8-2020

USE OF CITIZEN SCIENCE IN MONITORING GROUNDWATER QUALITY: A CASE STUDY FROM NEBRASKA

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MONITORING GROUNDWATER QUALITY:
A CASE STUDY FROM NEBRASKA

by

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Presented to the Faculty of

The Graduate College at the University of Nebraska

In partial Fulfillment of Requirements

For the degree of Master of Science

Major: Natural Resource Sciences

Under the supervision of Professor Daniel D. Snow

Lincoln, Nebraska

April, 2020

USE OF CITIZEN SCIENCE IN
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Citizen science has a key role in modernizing effective communication between professional scientists and the general public. However, citizen science differs to that of professional science due to equipment and experience and is a topic argued against citizen science. However, technology in water quality testing has developed in simplicity and affordability to a point where high school students, with hands-on training, can collect groundwater samples and test for quality themselves. Nebraska groundwater quality is a critical part of the state and can utilize high school students as citizen scientists for their communities. High school students from rural communities across Nebraska collected and tested groundwater for safe drinking water quality utilizing chemistry test kits. The samples were also sent to a professional laboratory to be tested for the same analytes the students tested and further correlated. High school students had such limitations that come with colorimetric chemistry kits whereas the professional laboratory utilized analytical instruments with trained and experienced staff. For five analytes, nitrate, chloride, calcium hardness, pH and electrical conductivity, similarities and differences were expressed in terms of the coefficient of determination (R^2) and the absolute difference in averages ($|\Delta ave|$). For Nitrate, the R^2 was 0.632 ±0.255, and the $|\Delta ave|$ of 3.97 ±5.32. A

comparison of the results between the citizen scientists and the professional scientists show similarities as well as areas for improvement. R^2 results for electrical conductivity were favorable where $|\Delta ave|$ results were not so favorable. $|\Delta ave|$ results for pH were favorable where R^2 results were not so favorable. Both R^2 and $|\Delta ave|$ results for nitrate were not polar opposites like results for pH and electrical conductivity.

Acknowledgements

I would like to thank the Nebraska Environmental Trust for funding this influential and far-reaching research endeavor. It has informed rural land owners and high school students and teachers, and it has informed leaders in local and state politicians, university professors and researchers, national and international organization. Funding was critical and without it, this research would not have been possible.

There were 18 high schools that participated in this project, but due to time constraints, data from 10 of those schools are included in the following research. I would like to thank all high schools: Auburn, Banner County, Callaway, Central City, Cody-Kilgore, Crawford, Freeman, Garden County, Kearney, Madison, McCook, McCool Junction, Newman Grove, Osmond, Sterling, Stuart, Superior and Waverly. The results of their participation will be protected in this research as the schools' names were replaced with alternate titles. Their hard-working science teachers and agricultural vocational teachers helped pave the way for the future of science and safe drinking water. I'd like to thank all the high school students that were able to participate and have hands-on experience in science literacy. I would also like to thank the rural well owners all over the state Nebraska for inviting local high school science projects onto their homes and giving students an opportunity to advance in science literacy.

I'd like to thank my advisor, Dr. Daniel D. Snow for entrusting me with such high caliber of a project that this research originates from. Whether the project was being productive or facing difficulties, his faith in me was unwavering. His academic and professional input affected the security of this research. I'd like to thank my graduate committee members, Drs. Mark Burbach and Matteo D'Alessio, for all their advice and input into making this research reach its potential, even when I fell far below all of its prerequisites. I'd like to thank the Nebraska Water Center, the Water Sciences

Laboratory, the College of Agriculture Sciences and Natural Resources, and the Department of Computer Science and Engineering for all their endeavors in making this research possible. The leadership, support and outreach from Drs. Chittaranjan Ray, Saptashati Biswas and Ashok Samal, as well as Matthew Kreifels, David Cassada, Jesse Starita, Shine Bedi and Nicole Schumacher.

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CHAPTER 1
INTRODUCTION

Water is not only essential to sustain life, but it also plays an integral role in ecosystem support, economic development, community well-being and cultural values (Gleick 1998). With nearly 71% of Earth's surface covered by water (USGS 2020), its quality is not less important than its quantity. About 99.3% of water on Earth is either saline water in the oceans (97.2%) or water stored in our ice caps and glaciers (2.1%) (Fetter 2018), making fresh water highly sought after and invaluable. Resources such as water with safe drinking quality are and will be stressed. Until recently, management of such natural resources was often the exclusive task of technical experts working under the auspices of the state (Pahl-Wostl 2009). However, as populations increase and sciences advance, the demands of research are outnumbering the capabilities of the state as the only decision-making authority. Awareness of uncertainty and change is increasing as new management practices that involve many stakeholders are being adopted (Pahl-Wostl 2009). As it is a necessity to human life, the largest and most important stakeholder group is the general public as the representatives of the humans who drink the water for sustenance. Instead of having business or government decision-makers at the forefront of water quality, the general public actively involved in knowing the quality of their own drinking water is a step towards developing effective water ethics and water security

(Postel 2013). Citizen science is one such path in getting the general public actively involved in learning about and appreciating the quality of their own drinking water.

Citizen science has constantly been redefined (Brouwer et al., 2018; Wiggins and Crowston 2011; Marshall, Lintott, and Fletcher 2015). Brouwer defined it as participation of the general public, i.e., non-scientists, in the generation of scientific knowledge. Wiggins and Crowston defined it as a collaborative research arrangement between experts and nonprofessionals, in which the nonprofessionals are involved in some aspect of the research process. Marshall and colleagues defined it as scientific research carried out by people who are not paid (citizens) but make intellectual contributions to scientific research nonetheless. Citizen science starts by taking into account that there are limited professional scientists who can collect data. With the utilization of the public as citizen scientists, theoretically, professional scientists can have observations and collections of various forms (i.e., samples, data, images, etc.), at various places both at the same time and at different times. Citizen scientists can collect and analyze more data than scientists alone (Conrad and Hilchey 2011). Citizen science is not just about collecting data. It's also a practice that can help us accomplish many goals, including a chance to harmonize the sciences and communities (Hannibal 2017). A deeper observation into citizen science is through its long-term effects on the success of science, the distribution of knowledge, decision making, both private and public, and two community, scientific and social.

In order for citizen science to succeed, it has to fulfill its scientific responsibilities. However, the success of science alone, comes from its roots in measurements. Nothing describes science better than Galileo Galilei's quote "*Measure* *what is measurable, and make measurable what is not so*" (Le-Gratiet et al., 2020). With so much emphasis placed on measuring, research on collective intelligence indicates that professional diversity is found in those doing the collection where new leaps of logic, innovation, and invention are more likely to arise (Dickinson et al., 2012). The successful distribution of data amongst the public participants and the professional scientists is a key goal of citizen science. The significance of data produced arguably might be the most highlighted emergence from these proactive citizens, more particularly from ongoing challenges and the desire for more combined and multidisciplinary solutions (Brouwer et al., 2018). With volumes of data now available in the palm of a hand via a smartphone, from the world wide web and from instant digital interactions, information is being spread at a far faster and more efficient way than before, as advances in telecommunication technology have led to a new type of citizen science (Brouwer et al., 2018).

1.1 Advantages in citizen science

There are a variety of potential advantages in having citizens measure, collect and analyze scientific data. One such benefit of citizen science is an increase in quantity of data being collected for various research purposes (Dickinson et al., 2012). Another advantage to citizen science is when there is a single research objective by a professional scientist through means of answering a single question, other stakeholders may benefit from the findings (Miller-Rushing et al., 2012).

Another benefit of utilizing citizen science is in the eventual and long-term impacts on the scientific, legal and social communities it involves (Jordan et al., 2012). There is a bridge of scientific and social knowledge shared between the scientific community and the general public. As the general public gets involved into various sciences, there is an educational effect on participants otherwise not implemented (Dickinson et al., 2012). This participation leads to educated choices in the public's future actions, policy implementations, and pursuit of scientific enlightenment. Ideally, a democracy will have a well-informed public to make better decisions to better its government (Durrance 1984; Mattson 1998). Equally, science should not be absent in order to have a well-informed public to make sound decisions. Citizen science has the potential to be effective in educating the public.

Citizen scientists can not only help by filling gaps with unlimited and adequate data, but also with funding due to volunteer practices and to the presence of an indispensable public interest in a variety of scientific fields. Prioritization and sustainability of natural resources raises the question of how government and private funding of scientific research can help society without referring to or involving public interest (Dickinson et al., 2012). Public interest is directly affected by citizen science projects because the public is directly involved in the research itself. Government and private funding of such scientific research can go further with limited funding due to volunteers. Public interest affects all scientific fields, and is not limited or narrow in topic. Data collected via citizen scientists are progressively used to monitor a wide range of resources including biodiversity, ecosystems and community health, marine and coastal resources, toxins, birds, water quality and quantity, trees and forests, and more (Chase and Levine 2016).

1.2 Disadvantages in citizen science

Many disadvantages have been reported within citizen science practices. Such disadvantages include unutilized data, data quality, challenges in communication, as well as management and organization. Projects involving citizen science may be able to collect a significant amount of scientific data, but that data will only be helpful if it is actually utilized (Kim et al., 2011). Data that is not utilized by professional scientists do not allow citizen science to make an impact in decision making (Figure 1) and may negate further funding of the citizen science endeavors. Scientists have a pivotal role in citizen science with responsibilities that, if overlooked, may harm citizen science as a whole. For example, research projects involving citizen scientists might have issues regarding data quality because citizens might have little to no training in scientific data management or research integrity, and therefore may not understand how to collect, record, or manage data properly (Resnik et al., 2015). For projects using citizen science to be successful, there needs to be constant and effective communication between the professional scientists and the citizen scientists in order for an understanding of what actions are being required and why these actions are necessary. Effective communication allows professional scientists to know what training is needed for successful data collection from citizen scientists. Such criticisms of citizen science projects regarding data quality implies that these often lack effective communication between the professional scientists and the citizen scientists. As a result, professionals may believe that citizen scientists are not committed or skilled enough to perform at the level of professional scientists (Kosmala et al., 2016).

However, the fault does not always lie on the shoulders of an enthused general public. Citizen science typically relies on volunteers, and the organizers need to have a thorough understanding of how to manage volunteers. Most organizations using citizen science lack the resources to conduct internal research and a thorough understanding of volunteer motivations to participate in citizen science projects (Alender 2015). The benefits of citizen science are many, but foremost is the actual scientific data being produced by the volunteering citizens. The focus of most projects using citizen science is therefore placed upon said benefits and not on understanding and helping the citizens making measurements and collecting data. The social value of citizen science is often ignored when the emphasis is only on the data produced. Little attention is paid to teaching and engaging citizen scientists, which can lead to misunderstandings or a lack of understanding of the purpose of the project. Other areas of disadvantages found in citizen science projects lie in ethical issues such as data sharing and intellectual property, conflict of interest and various forms of exploitation (Resnik et al., 2015). To avoid ethical mismanagement, some of the ways professional scientists can promote ethical research other than education and training is by developing guidelines for the involvement of citizens in research and by communicating effectively with participants at the beginning of each project (Resnik et al., 2015).

1.3 Citizen science and public awareness

Citizen science is an effective way to inform the public on issues that directly and indirectly influence decision making. Decision making on local, regional, national and international levels are becoming heavily influenced by the general public as seen on Figure 1 (Mckinley et al. 2017). Citizen science directly affects public input which directly affects decision making, reinforcing citizen science as an effective stepping stone in the decision making process. Citizen science is having an impact through data to aid decision making, as well as contributing to and participating in environmental governance (Craglia and Granell 2014). The effects of citizen science derived results do not stop at decision making alone. Policy proposals and voting are also affected by the consequences of citizen science. Globally, Non-Governmental Organizations and decision-makers increase the utilization of citizen scientists to enhance the ability to monitor and manage natural resources and the environment (Conrad and Hilchey 2011). Conrad and Hilchey provided some examples, one being Global Community Monitoring in which programs around the world, some with documented success like the *SIPCOT Area Community Environmental Monitors in India* assisted the establishment of national standards for toxic gases in ambient air. The impact of citizen science may not only affect decision making in government, but it may also affect decision making in science. Decision making can be affected at all levels ranging from countries and corporations to local community scales.

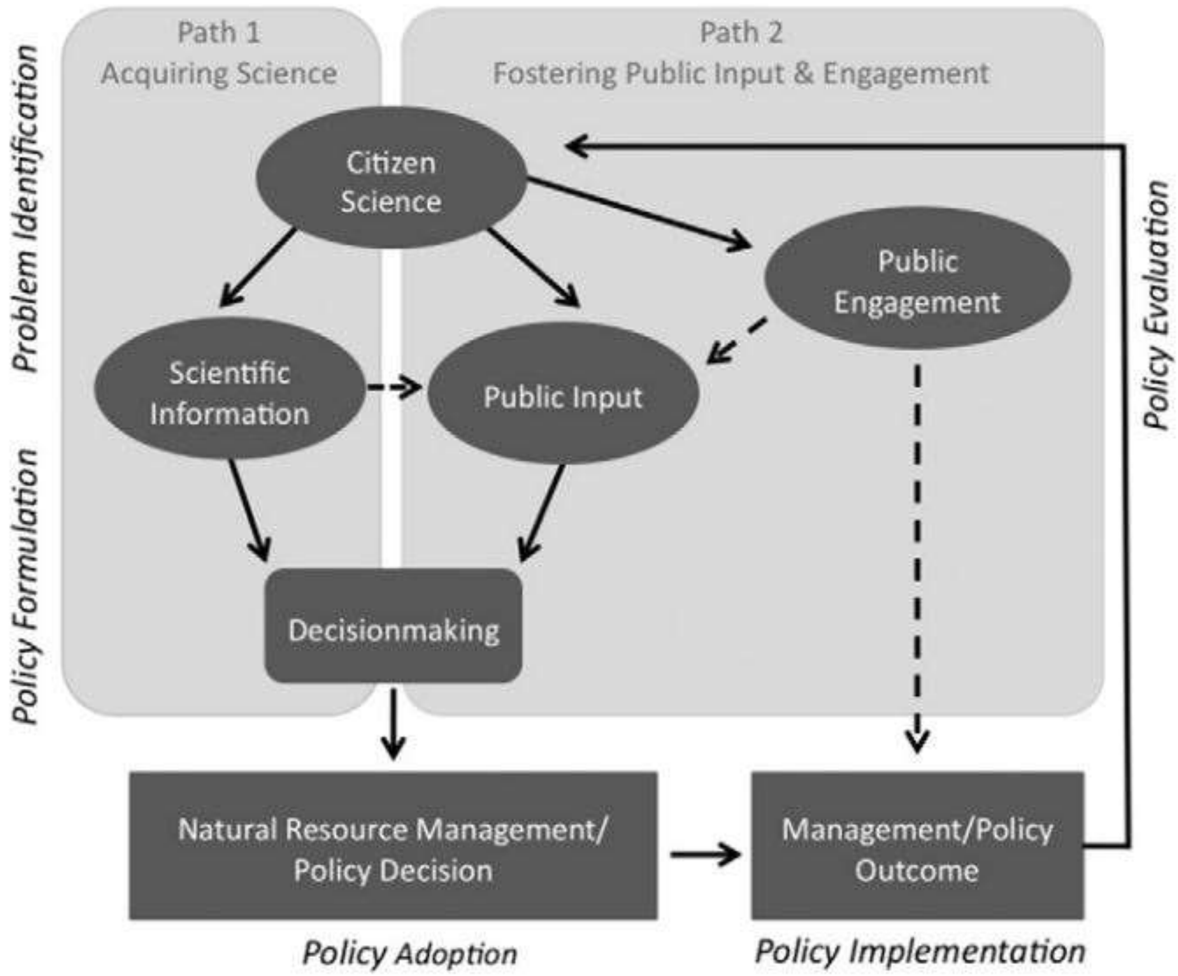

Figure 1. Impact of citizen science on society. The two pathways that citizen science can take to inform conservation, natural resource management and environmental protection by acquiring scientific information and fostering direct (solid arrows) and indirect (dashed arrows) public input and engagement (Source: Mckinley et al. 2017).

Citizen science has the potential to mend broken relationships of mistrust amongst various stakeholders in communities. The potential effects on the community resulting from activities in citizen science are that of social capital, community capacity, economic impact (job creation), and trust development between the public, scientists, and land managers (Jordan et al., 2012). However, from a traditional perspective, professional scientists and site or project managers tend to engage the community in a "one-way communicational model," limited to keep the community at a distance by limiting information which creates mistrust between scientists, regulatory officials and the affected communities (Ramirez-andreotta et al., 2015). Professionalization of the sciences has ousted amateur scientists for their lack of credibility and validation (Miller-Rushing et al., 2012). That credibility can be rebuilt with citizen science and bringing a communication model that all can participate in. On the professional perspective, citizen science programs have been noted as one way to augment limited resources and meet federal reporting requirements (Jalbert and Kinchy 2016). Public participation by the citizens in access to justice regarding environmental matters is a result that has come from the 1998 Aarhus Convention (Conrad and Hilchey 2011), empowering the community to build ownership and responsibility in natural resources. Citizen science benefits both the professional fields as well as the public at large.

1.4 Where citizen science has been applied

Environmental and life science research projects have widely used citizen science for its various benefits, often because the scale of these projects requires more resources than typically available. The longest known citizen science endeavor in the western hemisphere is in ornithology with the National Audubon Society's Annual Christmas Bird Count (CBC) which started at the turn of the 20th century (Dunn et al., 2005). The CBC has proactive citizens sign up in their local regions under a lead-count ornithologist. As beginners, new bird watchers are encouraged to join a group with a professional ornithologist to better understand what their responsibilities are as bird watching citizen scientists (“Christmas Bird Count” 2018). Data from such large geographic regions such as in the CBC are complicated due to variation in counts for summaries, such as multiple entries from the same location with different counts (Link et al., 2006). Ornithology based citizen science has been well documented in Costa Rica and Ethiopia (Şekercioĝlu 2012), across North America with the Avian Knowledge Network and Project FeederWatch (Caruana et al., 2006), the North American Breeding Bird Survey (Kosmala et al., 2016) and the Tucson Bird Count (Turner and Richter 2011; McCaffey 2005).

Examples of citizen science can be found in a variety of studies, including (Silvertown 2009), statistics (Isaac et al. 2014), psychology (Nov et al., 2011), astronomy (Marshall et al., 2015), computer science (Kawrykow et al., 2012), medicine (Ranard et al., 2013), and more (Alender 2015). Within water sciences, citizen science has been invaluable, with multiple projects in hydrology as well as surface water quantity and quality (Buytaert et al., 2014).

Although there are examples of citizen science use in hydrology, its scope has been limited. Complex and expensive devises and techniques are usually necessary for hydrologic measurements. Most citizen science projects have been limited to the monitoring of surface water quantity, quality and the measurement of precipitation (Grace-McCaskey et al., 2017). Few citizen science projects have been focused on groundwater. Additionally, citizen science projects tend not to be diverse (i.e. only activists) (Conrad and Hilchey, 2011). However, citizen science projects have utilized high school (HS) students rather than relying on activists. One example is found in

PowerStreams, a research-education-cooperation between a limnological research institute and five high schools in Austria (Weigelhofer et al., 2019). *PowerStreams* has high school students test surface water for the effects of agricultural land use on multiple in-stream processes. Having high school students as citizen scientists produced the needed large number of experiments for reliable estimations, but the students required extra supervision for safety and accuracy, as well as further simplification of concepts, instructions and equipment (Weigelhofer et al., 2019). Another example can be found in the *Groundwater Education Through Water Evaluation and Testing* (GET WET!) program started by Dr. Teresa Thornton and John Peckenham in Maine. This program has high school students become citizen scientists and test groundwater quality in private wells within their communities. GET WET! now is active at various locations within the United States (Orange County 2014; T. E. Thornton 2014).

1.5 Where citizen science has been avoided

Quality Assurance / Quality Control (QA/QC) requires that laboratories adopt a set of procedures to prove the legitimacy of test results (Ibe and Kullenberg, 1995). Ibe and Kullenberg (1995) state that selection of internationally-validated methodologies, reference material and intercomparison exercises make up QA/QC. Credible mechanisms that make up QA/QC generate the precision and accuracy that should be found in data is then used globally, regionally and nationally to protect the environment through regulation (Ibe and Kullenberg, 1995).

Effective QA/QC involving professional scientists in citizen science projects have been lacking. In order for data that has been collected, observed and analyzed by citizen science to be useful, it first must be trusted as a valid and reliable source (Thornton and Leahy 2012). Fundamentally, policy changes regarding quality protection are dependent on how end users trust the quality of the data collected (Peckenham and Peckenham 2014). Citizen science projects only have scientific impact when the collected data is used (Kim et al. 2011). One way to ensure data is more likely to be trusted is by including a QA/QC component that directly involves professional scientists with citizen science. In the GET-WET! program, high school students use a prepared laboratory standard for each test including chloride, hardness, total iron and nitrate. Additionally, they use commercially produced standards for pH and electrical conductivity (EC) tests (Peckenham and Peckenham 2014). These QA/QC components are performed by high school students and not professional scientists. For citizen science to be effectively trusted and further used in communities and in decision making, there needs to be a form of validation from professional scientists.

The use of QA/QC in citizen science projects need to be simplified and effectively explained to participants. QA/QC is an invaluable part of the scientific method and should not be rushed or partially completed. Examples of simple QA/QC are: having a professional laboratory test a sample that citizen scientists tested, have citizen scientists test the same sample twice and check for duplicate results, and have the citizen scientists test a blank sample with deionized/distilled water.

1.6 Motivation and contribution

The state of Nebraska has approximately 88% of residents relying on groundwater as their source of drinking water (NDEQ 2018). Approximately 20% of Nebraskan's rely on drinking water from private wells (Central District Health Department 2019) and few, if any, of these wells are regularly tested. Currently, there is no state or federal law mandating a requirement to test private domestic wells for water quality. This means that well owners lack any legal incentives to test their domestic wells for the quality of their own drinking water. Without such incentives, hazardous tendencies of avoiding or ignoring the practice of testing drinking water sources for quality may bring up an "out of sight, out of mind" attitude.

In 2018, Nebraska's market value of agriculture products sold was calculated at over 23 billion USD (USDA 2019). To effectively produce such high amounts of agricultural products, the influence of additional substances as fertilizers and pesticides are utilized. Often, historically high applications of agrichemicals in vulnerable areas impaired groundwater quality (Juntakut et al. 2019). With a heavy agricultural industry across the state, Nebraska has groundwater quality concerns that involve high nitrates, pesticides, bacteria and arsenic contamination, among others (NDEQ 2018).

Within rural communities across Nebraska, there continues to be a void between the scientific communities and the general public. With such institutions such as Nebraska's Natural Resources Districts and Extension, progress has been made in bridging this divide, but there is still better communication to develop. Citizen science offers an effective conversation of perspectives, ideas and data between groups, strengthening communication, cooperation and collaboration with scientific communities and the general public. With an impracticable probability of acquiring an additional professional workforce large enough to accomplish what citizen science can produce, both scientifically and socially, it's inconceivable to neglect the opportunity to utilize citizen scientists. Instead of utilizing activists, this unconventional citizen science approach, of informing and training multiple stakeholders (i.e. high school students, teachers and well owners in rural Nebraska), about how groundwater quality monitoring could greatly benefit the citizens, their health, agricultural industry and their land management practices.

The objectives of this research are: i) to evaluate how effective citizen science using high school students can be in monitoring groundwater quality, ii) to see which parameters tested by high school citizen scientists are most similar to their laboratory tested counterparts. I intend to submit one article, a case study, in the Journal of the American Water Resources Association.

CHAPTER 2

MATERIAL AND METHODS

High school (HS) identification

Public HSs in rural settings across Nebraska were identified separately by participants from 2017 and 2018. Participating HSs from 2017 were identified by specific science and Future Farmers of America (FFA) teachers who had a history of participating in joint HS – University of Nebraska-Lincoln (UNL) science projects and being within a 20 to 120 mile driving radius from UNL. Participating HSs from 2018 were identified by being within a 50 to 350 mile driving radius from UNL and either by science and FFA teachers having demonstrated an interest in joining the *Know Your Well* project, or science and FFA teachers who had a history of participating in joint HS – UNL science projects. Science/agricultural teachers from HSs meeting the above criteria were invited to take part in this hands-on research experience with their students. There were 4 participating HSs in the first year (2017) and 6 in the second year (2018). A total of 10 schools were involved in the data being compared to this research.

Training

Three visits to each school were needed at the beginning of each sampling campaign. The first visit is to introduce pre-field research, the second visit is to introduce field research, and the third visit is to introduce lab research. In the first visit, HS students were introduced to why and how to get involved in groundwater quality issues around their area and the importance of citizen science in water science studies. This includes highlighting the importance and urgency in knowing Nebraska's groundwater quality at a local level, and how to identify registered rural domestic wells around their communities. As pre-field research, students identified rural domestic wells within or near their communities by contacting the well owners and/or using the interactive online map available at the Nebraska Department of Natural Resources website (https://dnr.nebraska.gov/groundwater). Once the HS students identified suitable rural domestic wells, contacted the well owners, and verified their interest in participating in this study, a second visit was scheduled.

During the second visit, the students observed how scientists collect and test groundwater samples. Engaging teaching techniques can make a difference for the students and are based on instructional methods, including meaningful learning activities that engage students in the learning process (Prince 2004). Through this experience, students were able to i) observe domestic wells and their surrounding areas, ii) use scientific instrumentation to collect, preserve and store groundwater samples, and iii) use a digital approach to collect crucial data, like global positioning system (GPS) coordinates, through the Know Your Well App (https://itunes.apple.com/us/app/know-your-well/id1278672864?mt=8), the Know Your Well website (https://knowyourwell.unl.edu/welcome), an online questioner and a binder with a detailed questionnaire summarizing the different field activities (Appendix A).

During the third visit, students used chemistry kits (Table 1) to analyze collected groundwater samples, and observe the importance of recording results and the different methods to do so. Such methods included recording the results on paper, on the App, or with the online questioner found on the website. Student groups collected enough water samples to test 13 analytes; and as part of a QA/QC component, they sent each sample to the Water Sciences Laboratory (WSL) to be tested for the same analytes, eight of which are discussed in this research. By having a professional laboratory component for validation, results provide an opportunity for recommendations where citizen science in groundwater quality data was successful and where it needed improvement.

Table 1. Test kits and laboratory instrumentation used by citizen scientists (high school students) and professional scientists (WSL), respectively.

<table>
<tr><th colspan="3">Instrumentation
Citizen Scientists vs. Water Sciences Laboratory</th></tr>
<tr><th>Parameters</th><th>Citizen Scientists</th><th>Water Sciences Laboratory</th></tr>
<tr><td colspan="3">Basic Water Quality</td></tr>
<tr><td>pH</td><td rowspan="2">Hanna Instruments Multi-Parameter Tester</td><td>Fisher Scientific pH Meter</td></tr>
<tr><td>Electrical conductivity</td><td>Fisher Scientific Conductivity Meter</td></tr>
<tr><td>Hardness</td><td>CHEMetrix Calcium Hardness Test Kit</td><td>Estimated using Ca/Mg Equation</td></tr>
<tr><td colspan="3">Major Anions & Cations</td></tr>
<tr><td>Nitrate</td><td>CHEMetrix Nitrate Test Kit</td><td>AQ2 Discrete Analyzer</td></tr>
<tr><td>Chloride</td><td>HACH Chloride Test Kit</td><td>Ion Chromatograph</td></tr>
<tr><td>Calcium, Magnesium</td><td>N.a.</td><td>Atomic Absorption Spectroscopy</td></tr>
<tr><td colspan="3">Metals</td></tr>
<tr><td>Iron</td><td>CHEMetrix Iron Test Kit</td><td rowspan="3">Inductively Coupled Plasma Mass Spectrometry</td></tr>
<tr><td>Manganese</td><td>CHEMetrix Manganese Test Kit</td></tr>
<tr><td>Copper</td><td>CHEMetrix Copper Test Kit</td></tr>
</table>

With equipment to collect and test up to twenty samples, and following the first three visits, the students had enough experience to participate as citizen scientists. During each field activity, groundwater temperature, pH and conductivity were measured using a multi-parameter probe (Figure 2)(Appendix B). The probe was calibrated by the HS students using 7.0 pH and 1314 µS/cm electrical conductivity buffers. Following a survey (Appendix A) of the land and land-use near the well, the citizen scientists collected which were groundwater samples in analytically specific containers stored in portable coolers until they could be transferred to refrigerators with a 3-7 °C temperature. Groundwater samples were collected using a half-inch clear vinyl hose connected to the hydrant of the rural domestic well with a garden hose adapter. The hydrant was then turned on to continuously run water for approximately five minutes, to purge the stagnant water found in the groundwater plumbing system. After that, the citizen scientists filled four different bottles with groundwater. Two sample bottles, a 250mL Nalgene™ bottle and a 120 mL sterile plastic sampling bottle with an indicator line of 100mL, were kept with the citizen scientists, while two sample bottles, a 125mL Nalgene bottle, and a 1L glass amber bottle, were sent to/picked up/ brought to the WSL at UNL. The groundwater samples collected in the 125mL Nalgene bottle will be preserved with five drops (approximately 5mL) of hydrochloric acid (16M HCl). Samples were stored in a cooler during the transport to the HS and the WSL. Samples collected in the 250mL, 125mL and 1000mL bottles will be stored at 4°C before analysis, while samples collected in the 120mL bottle were immediately analyzed upon returning from the field.

Figure 2. Multimeters used by students to test for pH and electrical conductivity

One critically-important analyte the citizen scientists tested for was nitrate-N. The students utilized a CHEMetrics nitrate chemistry kit that uses colorimetric methods in producing a result. The lowest possible detection of nitrate in the sample is 4 mg/L. The next highest reference after 4 mg/L is 7 mg/L followed by 10 mg/L, 14 mg/L, 18 mg/L, 25 mg/L, 35 mg/L and its limit at 45 mg/L. The students had to make a visual judgment using the provided comparator displaying different shades of red to indicate different levels of nitrate in water (Figure 3). For comparison, the WSL was able to get results as low as 0.01 mg/L of nitrate-N using an autoanalyzer (AQ2, Seal Analytical, Mequon, WI) calibrated daily with standards and without the bias of a human eye. Similar techniques were practiced by the citizen scientists without analytical instrumentation on ammonia, Atrazine, chloride, copper, calcium hardness, iron, manganese, nitrite, total coliform and *E. coli*. Additional details regarding the analytical methodology practiced by the citizen scientists are given in Appendix B.

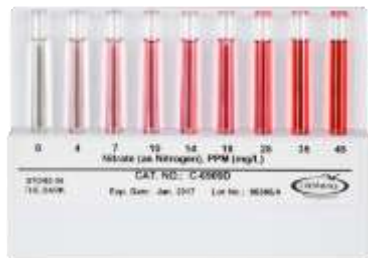

Figure 3. Indicator levels used by participating high school students. The provided CHEMetrics nitrate test kit had the lowest possible detection limit at 4 mg/L and its limit was 45 mg/L.

Each sample duplicate was then transported to the Water Sciences Laboratory (WSL) where it was tested for the same analytes using different methods and instruments appropriate in an environmental testing laboratory (Table 1). Unpreserved groundwater samples, stored in the 1L bottles, were used to measure major anions, pH, electrical conductivity and 18 pesticides. Preserved groundwater samples, stored in the 125mL bottles, were used to measure major cations, ammonia, nitrate, nitrite and metals. Additional details regarding the analytical methodology practiced by the professional laboratory are given in Appendix C.

As the citizen scientists submitted results regarding their water quality and the WSL produced their data from the same sample, similarities and differences in results were observed. Three separate approaches were used to compare the data produced by the student scientists to the laboratory methods. In the first scenario, i) the detection limits of the equipment being used by both citizen scientists and professional scientists have no effect on each other. As an example, pH, electrical conductivity, nitrate and chloride for both the citizen scientist and the WSL have results that can be observed and directly compared. In such cases, an estimate of the coefficient of determination was made by graphing the data and interpolating it linearly (Zhang 2017). The second scenario ii) was to observe the differences in average, where the total average for one analyte is recorded by the citizen scientists, subtracted by the total average of the results for that analyte by WSL. The closer the difference is to zero, the more similar the results are to one another. In the third scenario, iii) there is data that is not possible to directly correlate due to results being incomparable. This final challenge is due to the differences in detection limits on equipment being used (Table 2). As an example, copper, iron and manganese were detected in the µg/L (ppb) by WSL, whereas the citizen scientists measured in the mg/L (ppm). With a color correlation approach, a relationship of similarities and differences in the results were produced.

Table 2. Analytical detection limits of equipment used by the citizen scientists (high school students) and the professional scientists (WSL).

	Nitrate	**Hardness**	**Chloride**	**pH**	**EC**	**Copper**	**Iron**	**Manganese**
	mg/L	*mgCaCO*$_3$*/L*	*mg/L*		*µS/cm*	*mg/L*	*mg/L*	*mg/L*
High Schools	4	50	5	0.01	1	0.1	0.1	9
WSL	0.01	0.05	0.1	0.01	1	0.0001	0.00028	0.00019

To help correlate the data between HS and WSL, a visual interpretation of the concentrations measured will be utilized through box-whisker plots. The concentration distributions will be represented in percentiles (Figure 4). One percentile that will be used is the 90th percentile where everything below the 90th percentile mark represents 90% of the values submitted. The 90th percentile is observed in order to compare it between 90th percentiles that were produces from other data sets. Other percentiles that make up the rest of the observed box-whisker plot are the 75th, 50th (median), 25th, and 10th percentiles (Choo et al., 2020).

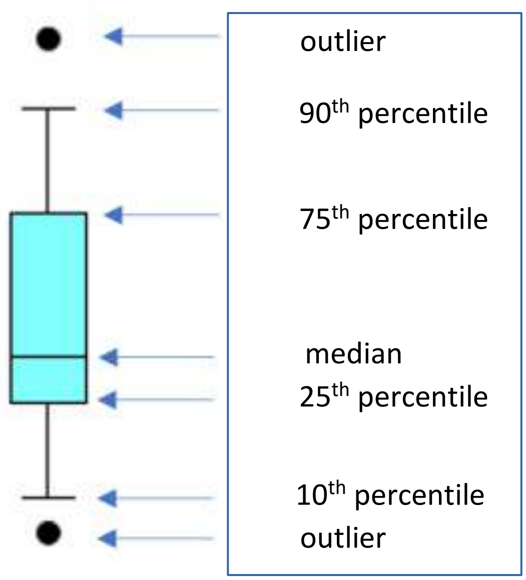

Figure 4. A summary of the assembly of a box-whisker plot.

CHAPTER 3
RESULTS & DISCUSSION

3.1 Coefficient of determination

The R^2 represents the proportion of variance explained by a linear model, ranging from 0-1 where the closer to 1, the more comparable the data (Nakagawa et al., 2017). Analyte concentrations within their method ranges and detection limits used in the R^2 approach for comparison: nitrate-N, calcium hardness, chloride, pH and EC. In comparing all nitrate-N measurements, the ten HSs had an average R^2 of 0.63 with samples ranging from 5 to 20 (Table 3). The group average R^2 and the standard deviation for the HS that participated in the first year was 0.57 and 0.34, respectively. The group average R^2 and the standard deviation for the HS that participated in the second year was 0.67 and 0.21, respectively. The highest individual R^2 value was 0.97 from Cottonwood HS with 20 samples, followed by a 0.91 from Aspen HS with 13 samples. The lowest R^2 value was 0.22 from Ash HS with 19 samples, followed by 0.34 from Sycamore HS with 10 samples. The school closest to the total average R^2 is Birch HS with an R^2 value of 0.59 and 7 samples, followed by 0.68 from Chestnut HS with 15 samples.

Table 3. Using data from samples tested for nitrate by both the high school students and WSL, a linear trendline can be produced with an R^2. An R^2 average and standard deviation were also produced for all schools in both years, as well as for the schools from Year 1 and Year 2. *n* is the number of samples being compared.

<table>
<tr><th colspan="10">Nitrate</th></tr>
<tr><th colspan="2">High School</th><th>a</th><th>b</th><th>R²</th><th>n</th><th colspan="2">R² Average</th><th colspan="2">Standard Deviation</th></tr>
<tr><td rowspan="4">Year 1</td><td>Oak</td><td>1.738</td><td>-3.113</td><td>0.811</td><td>20</td><td rowspan="4">0.572</td><td rowspan="10">0.632</td><td rowspan="4">0.339</td><td rowspan="10">0.255</td></tr>
<tr><td>Maple</td><td>0.764</td><td>6.723</td><td>0.344</td><td>18</td></tr>
<tr><td>Ash</td><td>0.562</td><td>6.514</td><td>0.223</td><td>19</td></tr>
<tr><td>Aspen</td><td>0.996</td><td>1.155</td><td>0.910</td><td>13</td></tr>
<tr><td rowspan="6">Year 2</td><td>Birch</td><td>1.039</td><td>2.920</td><td>0.589</td><td>7</td><td rowspan="6">0.672</td><td rowspan="6">0.208</td></tr>
<tr><td>Sycamore</td><td>0.548</td><td>0.305</td><td>0.335</td><td>10</td></tr>
<tr><td>Willow</td><td>1.113</td><td>2.061</td><td>0.722</td><td>16</td></tr>
<tr><td>Chestnut</td><td>0.506</td><td>4.013</td><td>0.683</td><td>15</td></tr>
<tr><td>Cottonwood</td><td>0.977</td><td>1.093</td><td>0.971</td><td>20</td></tr>
<tr><td>Elm</td><td>0.783</td><td>0.487</td><td>0.733</td><td>5</td></tr>
</table>

Comparing R^2 for calcium hardness measurements, all ten HSs had an average R^2 of 0.38 with samples ranging from 4 to 20 (Appendix D). The average R^2 for the HS that participated in the first year and second year were 0.35 and 0.40, respectively. The highest R^2 value was 0.89 from Elm HS with 4 samples, followed by a 0.80 from Oak HS with 20 samples. The lowest R^2 value was 0.001 from Sycamore HS with 10 samples, followed by 0.03 from Ash HS with 19 samples. The school closest to the total average R^2 is Maple HS with an R^2 value of 0.33 and 18 samples.

The R^2 for chloride comparing measurements for ten HSs had an average R^2 of 0.37 with samples ranging from 6 to 20 (Appendix D). The average R^2 for the HSs that participated in the first year and second year were 0.50 and 0.28, respectively. The highest R^2 value was 0.99 from Oak HS with 20 samples, followed by a 0.82 from

Cottonwood HS with 20 samples. The lowest R^2 value was 0.02 from Birch HS with 7 samples, followed by 0.07 from Chestnut HS with 11 samples. The school closest to the total average R^2 is Maple HS with an R^2 value of 0.39 and 18 samples, followed by 0.54 from Willow HS with 16 samples.

The R^2 for pH comparing measurements for ten HSs had an average R^2 of 0.27 with samples ranging from 4 to 20 (Appendix D). The average R^2 for the HSs that participated in the first year and second year were 0.31 and 0.24, respectively. The highest R^2 value was 0.69 from Elm HS with 7 samples, followed by a 0.67 from Ash HS with 4 samples. The lowest R^2 value was 0 from Willow HS with 14 samples, followed by 0.001 from Cottonwood HS with 20 samples. The school closest to the total average R^2 is Maple HS with an R^2 value of 0.24 and 16 samples, followed by 0.19 from Oak HS with 20 samples.

The R^2 for EC comparing measurements for ten HSs that participated had an average R^2 of 0.82 with samples ranging from 2 to 20 (Appendix D). The average R^2 for the HSs that participated in the first year and second year were 0.71 and 0.90, respectively. The highest R^2 value was 1.00 from Ash HS with 2 samples, followed by a 0.95 from Willow HS with 14 samples. The lowest R^2 value was 0.12 from Aspen HS with 14 samples, followed by 0.80 from Maple HS with 16 samples. The school closest to the total average R^2 is Birch HS with an R^2 value of 0.84 and 13 samples, followed by 0.80 from Maple HS with 16 samples.

3.2 Differences in averages

A second approach used to compare the same five analytes is through taking the differences in averages. The purpose of using this method is to have a comparison to the results from R^2. With the differences in average, the closer the results are to zero, the more similar the results from the HSs and WSL are similar to one another. Analytes with a larger range will have differences in average much higher than those with lower ranges. Regarding nitrate-N, the range of difference in average was from 11.25 to 1.18. The differences in average that came closest to 0 are 1.18 from Aspen with 13 samples, followed by 1.35 from Elm with 5 samples, and 1.38 from Sycamore with 10 samples (Table 4). Aspen, Elm and Sycamore showed standard deviations of 1.54, 0.60, and 1.29, respectively. The differences in average that were furthest from 0 are 11.25 from Ash with 19 samples, followed by 6.74 from Maple with 18 samples, and 5.24 from Oak with 20 samples. Ash, Maple, and Oak showed standard deviations of 13.27, 7.97, and 11.42, respectively (Table 4).

Table 4. Using data from samples tested for nitrate-N by both the high school students and WSL, an average was produced. The average for the results of the high school students was then subtracted from the average for the results of WSL. The closer the differences in average are to 0, the more similar they are. The R^2, standard deviation and number of samples (n) is displayed for observational purposes. *n* is the number of samples being compared.

Nitrate			**|WSL - HS|**		**n**
High School		**R^2**	**Diff. in average**	**Stand. Dev.**	
Year 1	Oak	0.811	5.24	11.42	20
	Maple	0.344	6.74	7.95	18
	Ash	0.223	11.25	13.27	19
	Aspen	0.910	1.18	1.54	13
Year 2	Birch	0.589	3.19	5.83	7
	Sycamore	0.335	1.38	1.29	10
	Willow	0.722	3.50	4.48	16
	Chestnut	0.683	4.45	5.46	15
	Cottonwood	0.971	1.40	1.38	20
	Elm	0.733	1.35	0.60	5

In comparing calcium hardness measurements, the range of results produced by the difference in average was from 211.76 to 10.80. The differences in average that came closest to 0 are 10.80 from Elm with 4 samples, followed by 39.86 from Birch with 7 samples, and 70.19 from Chestnut with 15 samples (Appendix D). Elm, Birch and Chestnut showed standard deviations of 8.54, 80.23, and 70.78, respectively. The differences in average that were furthest from 0 are 211.76 from Willow with 16 samples, followed by 172.24 from Sycamore with 10 samples, and 170.09 from Oak with 20 samples. Willow, Sycamore, and Oak showed standard deviations of 128.66, 177.04, and 144.31, respectively (Appendix D).

In comparing chloride measurements, the range of results produced by the difference in average was from 56.80 to 21.39. The differences in average that came closest to 0 are 21.39 from Sycamore with 10 samples, followed by 22.32 from Willow with 16 samples, and 23.03 from Cottonwood with 20 samples (Appendix D). Sycamore, Willow and Cottonwood showed standard deviations of 10.73, 13.08, and 18.68, respectively. The differences in average that were furthest from 0 are 56.80 from Ash with 19 samples, followed by 49.81 from Elm with 6 samples, and 43.94 from Aspen with 14 samples. Ash, Maple, and Oak showed standard deviations of 29.11, 26.10, and 72.14, respectively (Appendix D).

In comparing pH measurements, the range of results produced by the difference in averages was from 2.15 to 0.17. The differences in average that came closest to 0 are 0.17 from Chestnut with 18 samples, followed by 0.20 from Cottonwood with 20 samples, and 0.21 from Birch with 13 samples (Appendix D). Chestnut, Cottonwood and Birch showed standard deviations of 0.18, 0.22, and 0.29, respectively. The differences in average that were furthest from 0 are 2.15 from Ash with 4 samples, followed by 0.89 from Aspen with 14 samples, and 0.86 from Willow with 14 samples. Ash, Aspen, and Willow showed standard deviations of 3.76, 0.62, and 2.65, respectively (Appendix D).

In comparing EC measurements, the range of results produced by the difference in average was from 416.54 to 38.71. The differences in average that came closest to 0 are 38.71 from Elm with 7 samples, followed by 76.17 from Chestnut with 18 samples, and 102.27 from Birch with 13 samples (Appendix D). Chestnut, Cottonwood and Birch showed standard deviations of 30.57, 48.92, and 144.54, respectively. The differences in average that were furthest from 0 are 416.54 from Aspen with 14 samples, followed by 178.38 from Maple with 16 samples, and 139.79 from Willow with 14 samples. Ash, Aspen, and Willow showed standard deviations of 240.98, 161.70, and 63.67, respectively (Appendix D).

3.3 Color correlation

Data collected yet not able to be directly correlated using R^2, was analyzed using an alternative color correlation due to differences in sensitivity of results. Results that were produced by the HSs had to be within +/- 0.05 mg/L of the result produced by WSL to be considered in agreement. Regarding copper, Oak HS was able to collect 20 samples. All 20 samples tested by the students were in agreement with the results produced by WSL (Table 5). On the color correlation table (Table 6), Oak HS was able to reach 100%, with 20 out of 20 samples in agreement, whereas Ash HS was able to 74% with 14 of 19 total samples in agreement. Five of the ten HSs were able to reach 100% in the copper color correlation, each with varying amounts of samples analyzed. The most samples analyzed was 20 from both Oak and Cottonwood HSs. The fewest samples analyzed was seven from both Birch and Elm HSs. The average for all ten schools was 93.6%, where the first year's average was 88.8% and the second year's average was 96.8%.

Table 5. Samples tested for copper, iron and manganese by both WSL and HS. These were then compared to the number of HS samples that tested to be within range (WR) of the WSL results.

Schools	Copper		Iron		Manganese	
	n **in agreement**	***n*** **analyzed by WSL & HS**	***n*** **in agreement**	***n*** **analyzed by WSL & HS**	***n*** **in agreement**	***n*** **analyzed by WSL & HS**
Oak	20	20	14	20	20	20
Maple	16	18	16	18	18	18
Ash	14	19	18	19	17	19
Aspen	12	13	10	13	13	13
Birch	7	7	7	7	7	7
Sycamore	10	10	7	10	10	10
Willow	16	16	12	16	16	16
Chestnut	12	14	16	17	12	13
Cottonwood	19	20	20	20	20	20
Elm	7	7	7	7	6	6
WSL instruments –> 0.001 mg/L =1 µg/L, HS instruments –> 0.1 mg/L						

Table 6. Color correlation from results found on Table 5, where green is the 100% WR and varying degrees of yellow and orange down to red which is the lowest at 70% WR.

Schools	Copper	Iron	Manganese
Oak	100	70	100
Maple	89	89	100
Ash	74	95	89
Aspen	92	77	100
Birch	100	100	100
Sycamore	100	70	100
Willow	100	75	100
Chestnut	86	94	92
Cottonwood	95	100	100
Elm	100	100	100

Regarding iron, Cottonwood HS was able to collect 20 samples. All 20 samples tested by the students were in agreement with the results produced by WSL (Table 5). On the color correlation table (Table 6), Oak HS was able to reach 100%, with 20 out of

20 samples in agreement, whereas Oak HS was able to 70% with 14 of 20 total samples in agreement. Three of the ten HSs were able to reach 100% in the iron color correlation, each with varying amounts of samples analyzed. The most samples analyzed were 20 from both Oak and Cottonwood HSs. The fewest samples analyzed were seven from both Birch and Elm HSs. The average for all ten schools was 87.0%, where the first year's average was 82.8% and the second year's average was 89.8%.

Regarding manganese, both Oak and Cottonwood HSs were able to collect 20 samples. All 20 samples from both schools tested by the students were in agreement with the results produced by WSL (Table 5). On the color correlation table (Table 6), both Oak and Cottonwood HSs were able to reach 100%, with 20 out of 20 samples in agreement, whereas Ash HS was able to 89% with 17 of 19 total samples in agreement. Eight of the ten HSs were able to reach 100% in the manganese color correlation, each with varying amounts of samples analyzed. The most samples analyzed were 20 from both Oak and Cottonwood HSs. The fewest samples analyzed were six from Elm HS. The average for all ten schools was 98.1%, where the first year's average was 97.3% and the second year's average was 98.7%.

3.4 Nitrate-N

Using a box-whisker plot as a visualization method for nitrate-N results, paired measurements allow a variety of observations (Figure 5). For example, each WSL's 50^{th}

percentile, also known as the median, may not be the same as their paired HS's median. The medians, however, do not fall outside the 75th and 25th percentiles of their paired data sets, which is desirable. The same can be said about the 75th percentiles of one data set not falling outside their paired data set's 90th percentiles. This is also mirrored on the lower percentiles. Although the box-whisker plots may show that each HS is different than their WSL counterpart, they also show similarities in concentration ranges.

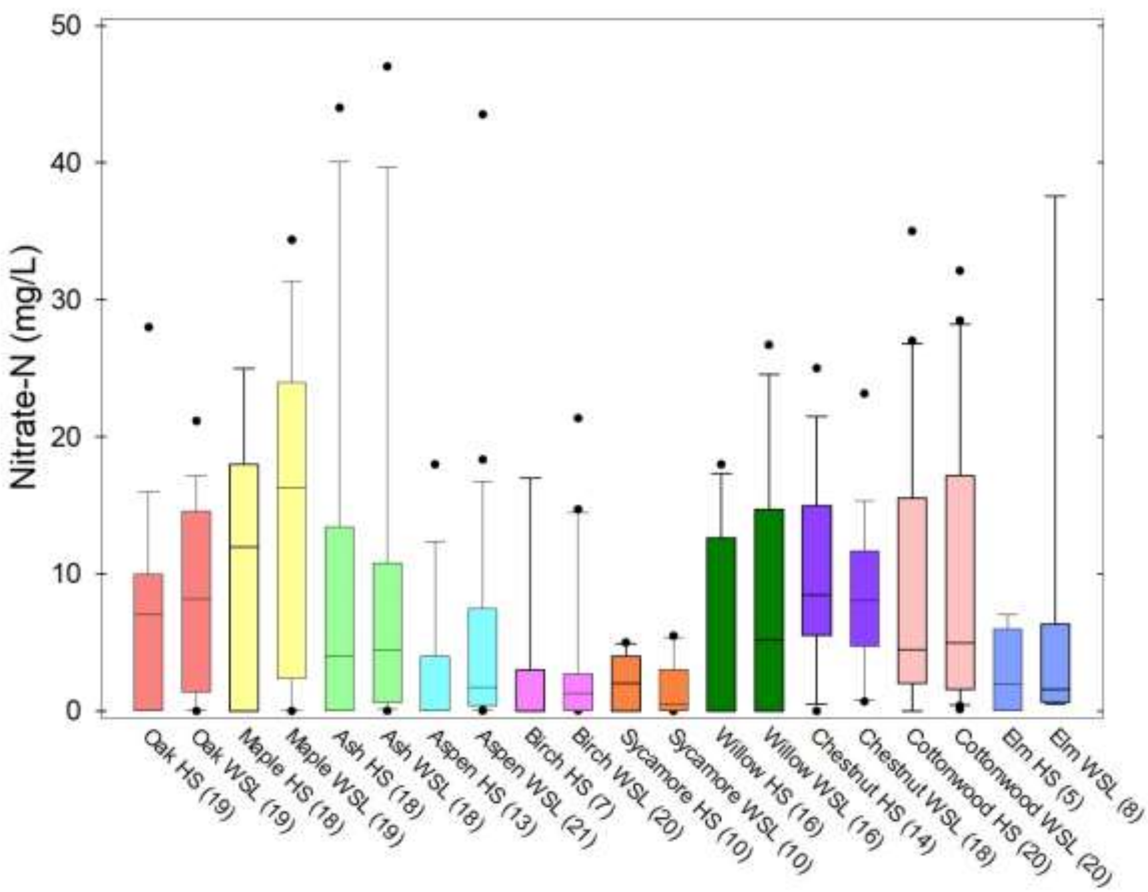

Figure 5. Nitrate-N results expressed as box-whisker plots for each locations' High School and Water Sciences Laboratory. High School (*n*) where *n* is the number of samples being compared.

There are missing medians found in Figure 5 due to a combination of minimal results submitted with a majority of those results being zero. Three HS box-whisker plots are missing medians. Aspen HS reported 13 results, 9 of which were zeros. The HS had limitations on results, one such limitation was the range of detection being between 4 and 45 mg/L without the practice of dilution. A value below 4 mg/L proved to be challenging to detect and were recorded as zero. This explains a high number of results being reported as zero. This affects the box-whisker plot, as it does not express a median on its display. Birch and Willow HS share such examples of reported zeros and their box-whisker plots and lack medians. This was not the case with data reported from WSL due to the 0.01 mg/L detection limit.

Limitations in measurement methods between HS and WSL offer an explanation for the observable differences in results. Differences such as analytical instrumentation and simplified test kits, and with differences in detection, results can be observed, such as Oak HS's first sample (Figure 6). This sample was collected and tested for nitrate as 7 mg/L by the students and 8.16 mg/L by WSL. The HS did not have analytical instrumentation to produce a result equal to that of WSL's 8.16 mg/L. They were given the detection examples of 4, 7, 10, 14, 18, 25, 35 and 45 mg/L without any training or education on dilution. The HS's choice of 7 mg/L was the closest to what eventually the WSL tested for. Even with differences in testing techniques, this is an example of how similar the results came to be. However, not all results were as similar. For example, Ash

HS reported a sample as low as 4 mg/L by the students, yet when further tested by WSL, it was measured at 47.0 mg/L (Figure 7). Another approach used in detection technique was where the students could not decide the result upon the provided detection examples of 4, 7, 10, 14, 18, 25, 35 and 45 mg/L. Students would choose in between the detection examples, such as 12 and 16 mg/L. As a result, as seen on Figure 8, where all schools' results for nitrate-N are observed, results are concentrated around 0, 4, 7, 10, 14, and 25 mg/L. Such concentration of data occurred because of the limitation of choices the students had based on the suggested detection examples provided in the chemistry kits the students used.

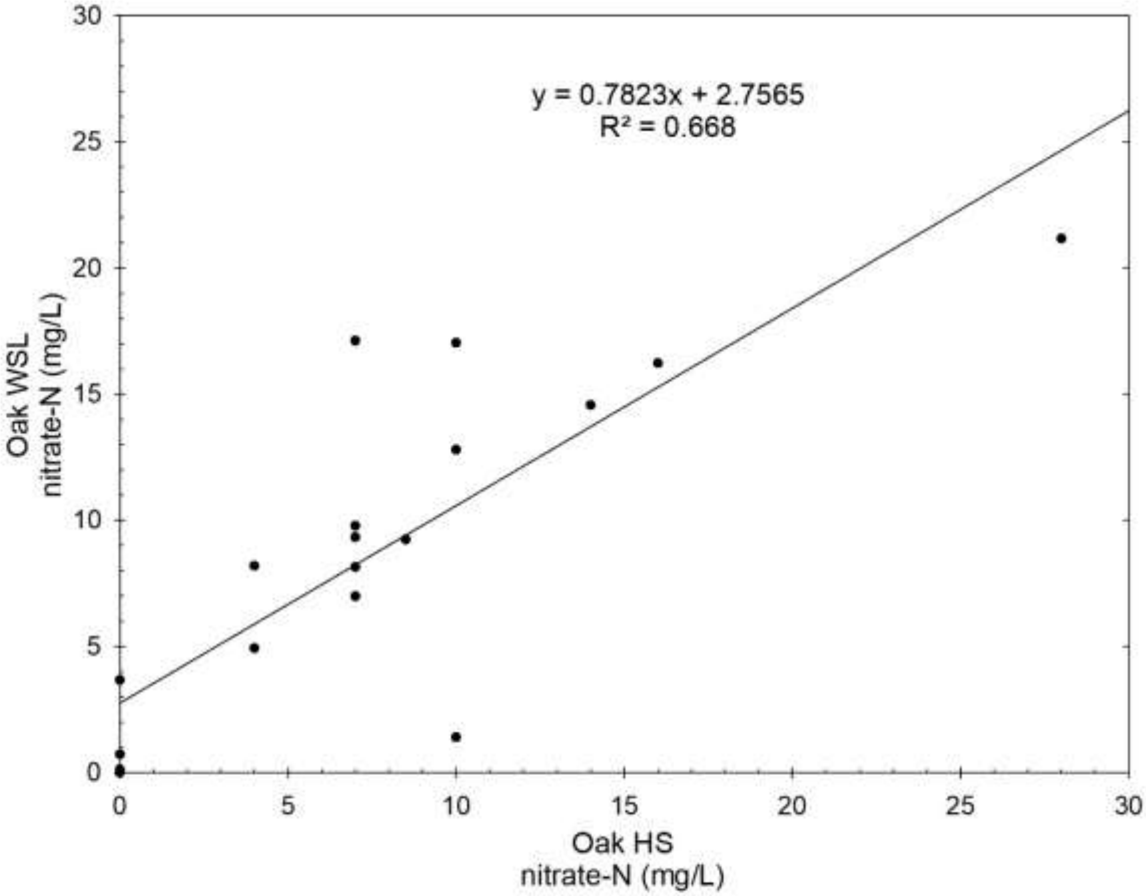

Figure 6. Oak nitrate-N expressed as a scatter-plot of result comparisons between Oak high school and the Water Sciences Laboratory.

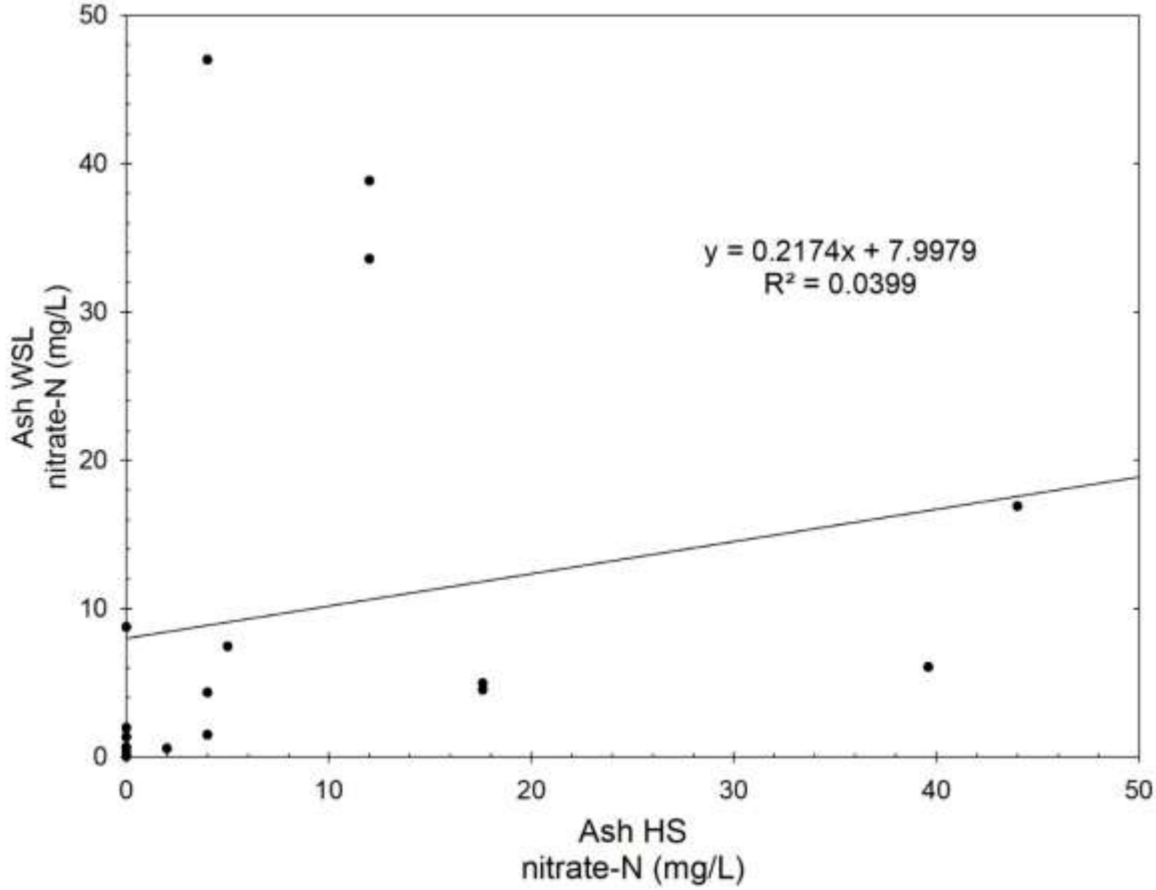

Figure 7. Ash nitrate-N expressed as a scatter-plot of result comparisons between Ash high school and the Water Sciences Laboratory.

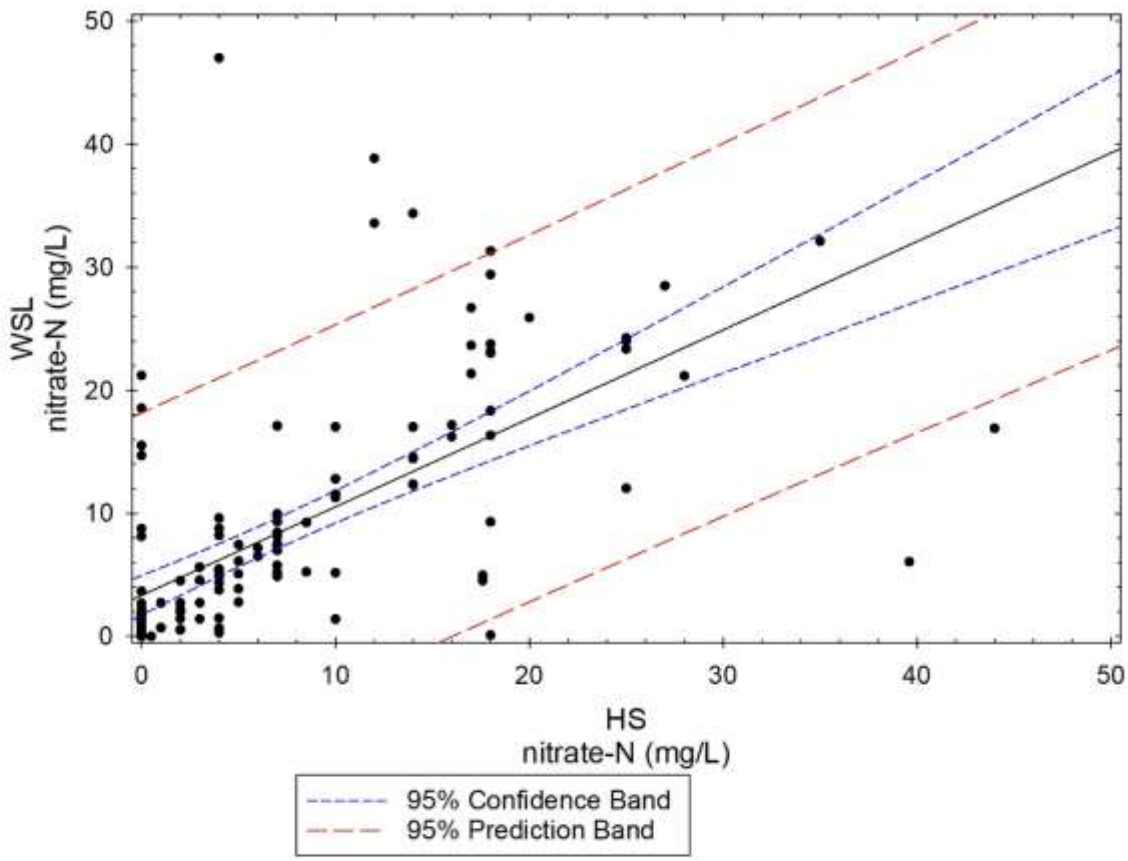

Figure 8. All schools nitrate-N expressed on one scatter-plot with confidence and prediction bands.

For nitrate-N, the number of samples (*n*) had a lack of influence on the estimate of the coefficient of determination (R^2) results. Both Cottonwood and Oak produced results for 20 samples each, with an R^2 result of 0.97 and 0.81, respectively. However, both Ash and Maple produced results for 19 and 18 samples, respectively, each with an R^2 result of 0.22 and 0.34, respectively. To add to this observation, Birch, Sycamore, Elm and Aspen were the four schools that had the lowest *n* values ranging from 5 to 13 samples, with R^2

results ranging from 0.34 to 0.91. Calcium hardness, pH and electrical conductivity (EC) showed a similar trend.

Differences in R^2 between the schools participating in the first year vs the second year vary. The average of R^2 values for nitrate-N is higher from schools who participated in the second year with an R^2 average of 0.67 whereas the first year had an average of 0.57, both having averages above the 0.50 mark. The differences in averages between HS and WSL ($|\Delta ave|$ = |HS average – WSL average|) is a means of correlation dissimilar to R^2, and in nitrate-N ranges from a 45 maximum to an ideal minimum of zero, with a 22.5 as a middle marker, by definition. The lowest $|\Delta ave|$ was 1.3 from Sycamore HS while the highest $|\Delta ave|$ was 11.0 from Ash. The average from all ten schools was 3.6.

3.5 Calcium Hardness

Calcium hardness in water, like nitrate-N concentration, was determined by students using their visual judgment of the color in the chemical reaction and the indication levels of calcium hardness in mg/L. The difference was in the use of what the calcium hardness kit called a control bar, where operating it was prone to human error. Because of this added human error, the median for each HS was consistently less than the median for their paired WSL (Figure 9). The range for the calcium hardness kit that the students used was from 50 mg/L to 500 mg/L and a concentration of results can be seen on each 50, 200, 250, 350 and 500 mg/L, which were suggested indication levels for calcium hardness in the sample (Figure 10).

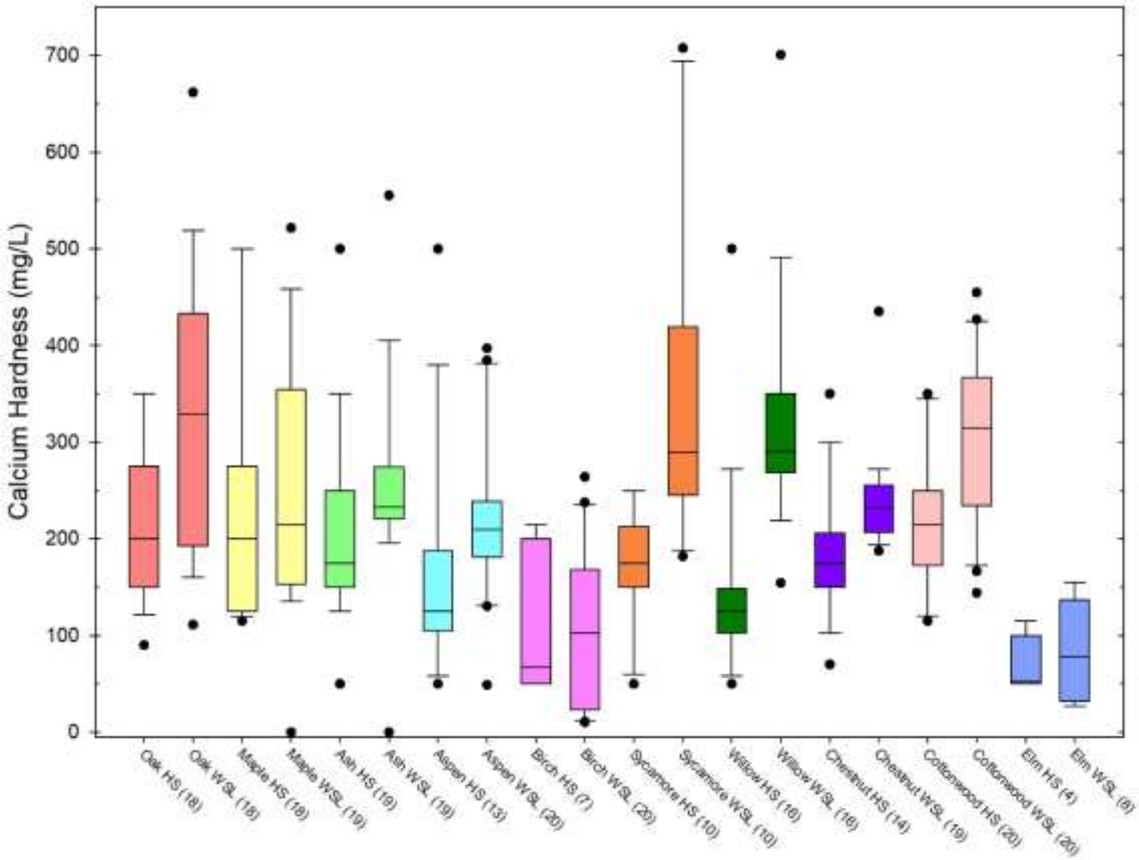

Figure 9. Calcium hardness results expressed as box-whisker plots for each locations' High School and Water Sciences Laboratory.

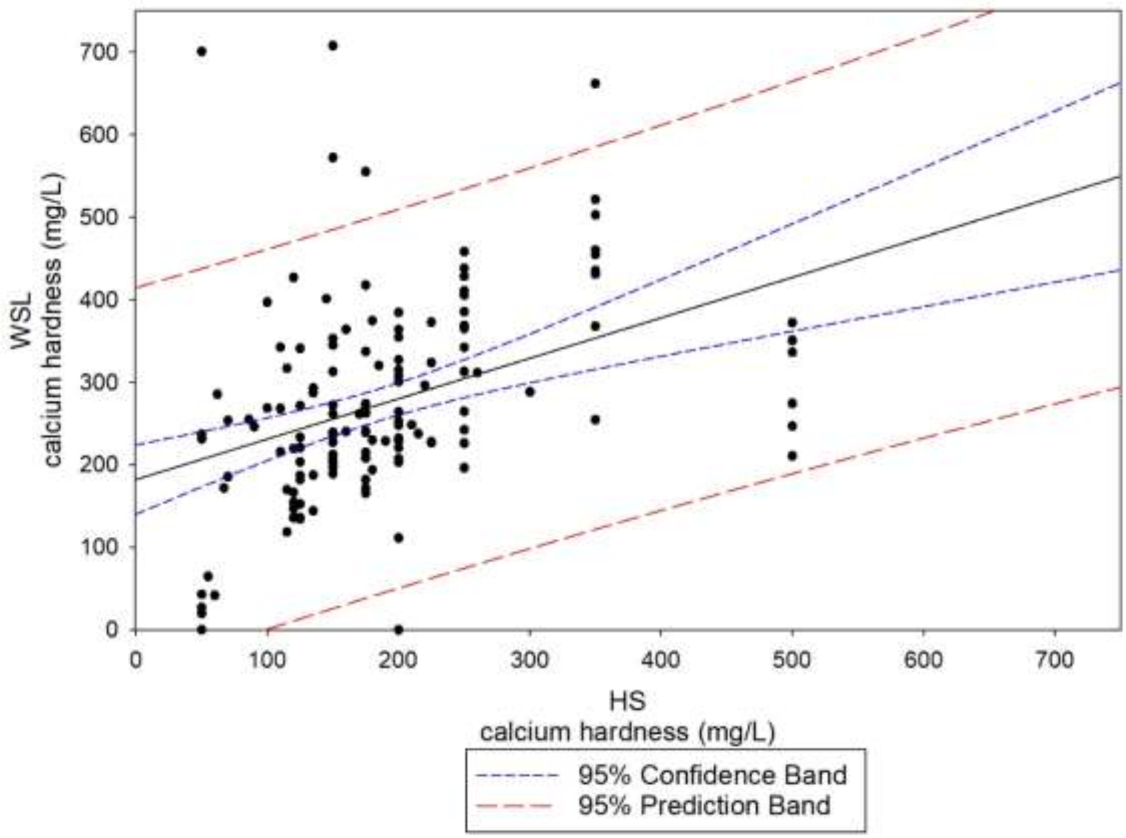

Figure 10. All schools calcium hardness expressed on one scatter-plot with confidence and prediction bands.

The average R^2 values for calcium hardness is higher from schools that participated in the second year with an R^2 average of 0.40 where the first year had an average of 0.35, both having averages below the 0.50 mark. Due to the control bar in the kit the students used, added to the variability of eyes from various students, and instructions that were not intended for a targeted audience of HS students, the calcium hardness kit proved to be challenging for HS. The lowest |Δave| was 10.8 from Elm HS while the highest |Δave| was 211.8 from Willow HS. The average of all ten schools was 108.9. The nitrate-N R^2 values turned out to be higher than the calcium hardness R^2 values due to the control bar as an added potential to human error, but also to a higher range, where nitrate-N went from 4-45 mg/L, calcium hardness went from 50 to 500 mg/L.

3.6 Chloride

For chloride, *n* did have an influence on the R^2. Both Oak and Cottonwood produced results for 20 samples, each with an R^2 result of 0.99 and 0.82, respectively, and were the two highest R^2 values. Both Elm and Birch produced results for 6 and 7 samples, respectively, each with an R^2 result of 0.03 and 0.02, and were the two lowest R^2 values. Five schools with the highest *n* values, which were Oak, Cottonwood, Ash, Maple and Willow, ranged from 16 to 20, each had higher R^2 values, ranging from 0.99 to 0.39. In comparison, the five schools with the lowest *n* values, ranged from 6 to 14, which were Aspen, Chestnut, Sycamore, Birch and Elm, had an R^2 value ranging from 0.02 to 0.2.

The average R^2 value for chloride is higher from schools who participated in the first year with an R^2 average of 0.50 compared to the second year with an average of 0.28. Students had to make a visual judgment on how many drops through titration it took the sample to transition into a vague "rust orange" color. With different students interpreting what the ideal "rust orange" color might be, an optically opinionated answer was provided. Each HS produced results higher than the WSL (Figure 11) due to the uncertainty of what “rusty orange” looks like. The is an observable grouping bellow 100 mg/L (Figure 12), with 5 samples recorded as being more than 100 mg/L by the students. Where calcium hardness had a very sensitive process, chloride had was lacking sensitivity. The students often went too far in titration because the “rust orange” color was not yet observed. Yet with titration, an additional drop would already surpass the “rust orange” color, making the students more confident that they have reached the required “rust orange” color.

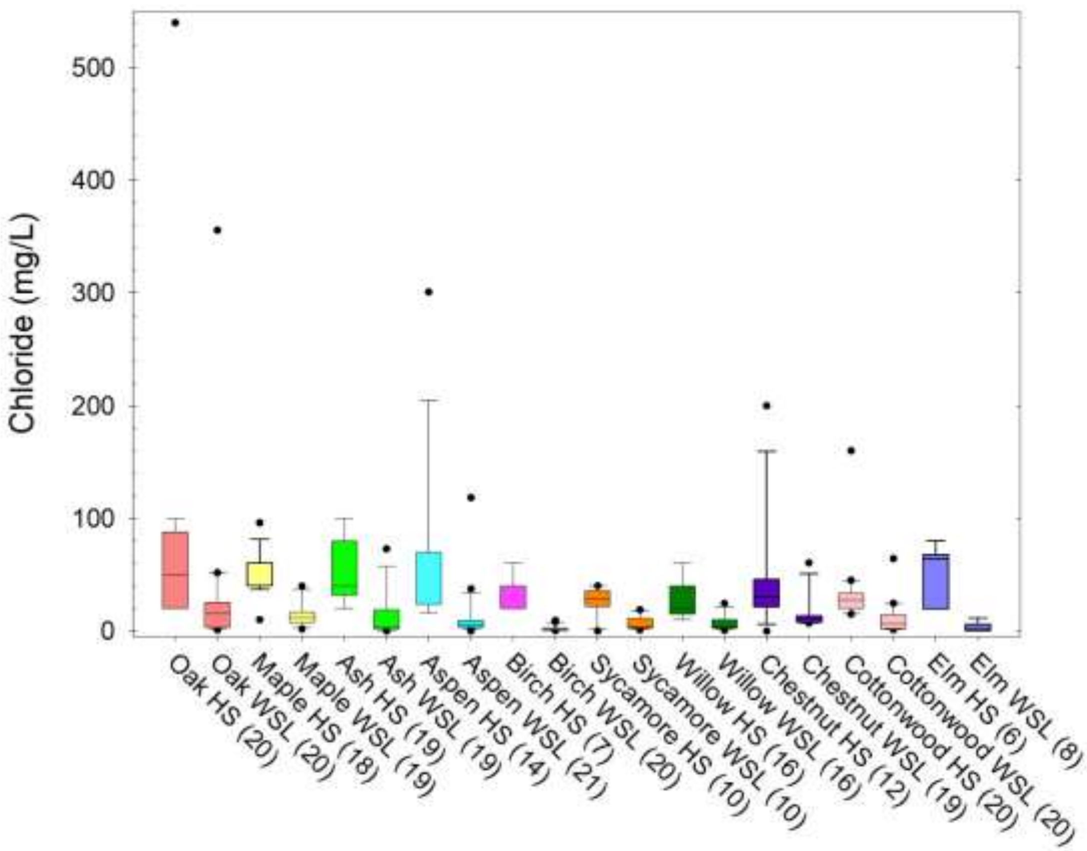

Figure 11. Chloride results expressed as box-whisker plots for each locations’ High School and Water Sciences Laboratory.

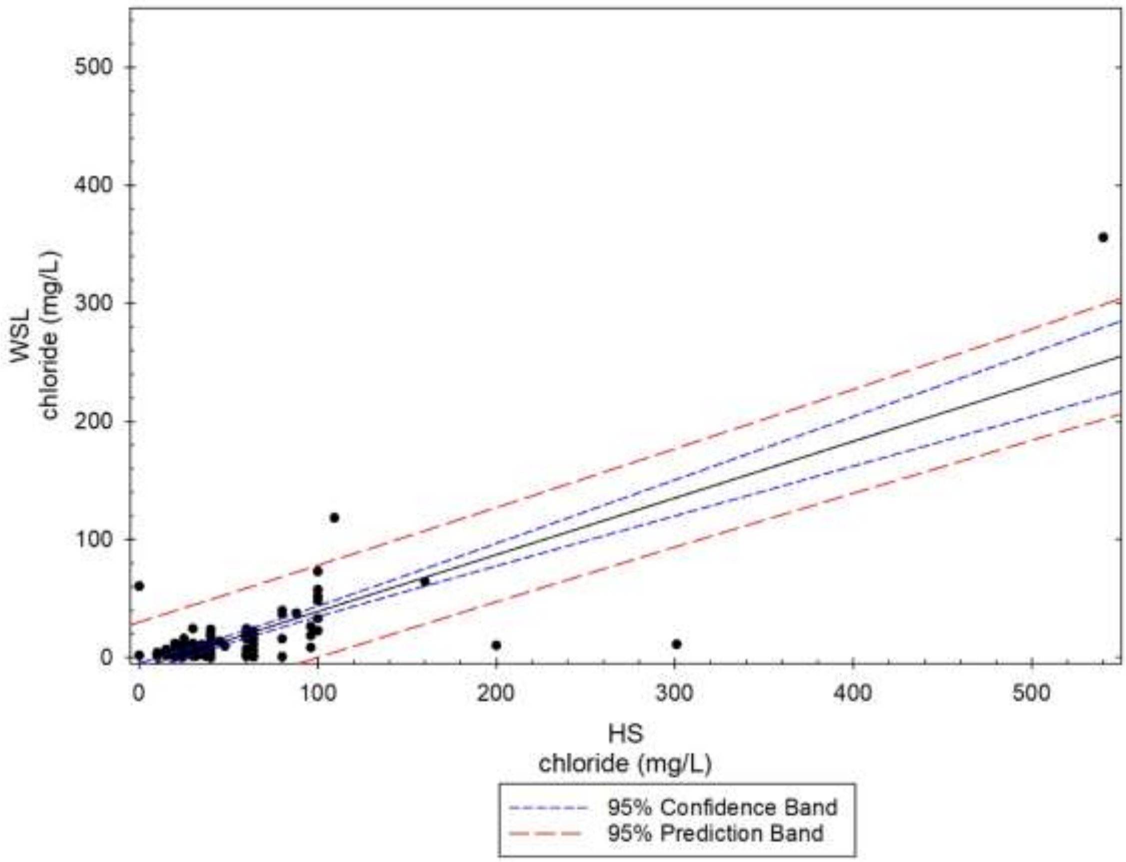

Figure 12. All schools chloride expressed on one scatter-plot with confidence and prediction bands.

The |Δave| showed a different perspective of the correlation. Where nitrate-N had desirable correlation both in R^2 and |Δave|, >0.50 and <40.0, respectively, and calcium hardness had undesirable correlation both in R^2 and |Δave|, chloride had undesirable correlation in R^2, and desirable correlation in |Δave|. The R^2 average for both years was

0.35, while the average for |Δave| was 37.0. Both correlation approaches may not always agree.

3.7 pH & EC

In contrast to the other measured water quality parameters, a probe was used to measure pH and EC by the students as well as the WSL. HS students used a multimeter probe capable of measuring pH, EC and temperature, while individual probes were used at the WSL. By using a probe, the errors associated to the test kits were removed. The R^2 average for all ten schools was 0.27 with the first year's average being 0.30 and the second year's average being 0.24. Similar to chloride, the |Δave| proved to be different than the R^2. The |Δave| had an average of 0.56 for all ten schools. This is in part due to the short range of results from 6.15 to 8.38, making the |Δave| very small. In contrast, EC's R^2 average for all ten schools was 0.82 with the first year's average being 0.71 and the second year's average being 0.90. The |Δave| proved to be different than the R^2, yet opposite to pH and chloride. The |Δave| had an average of 147.5 for all ten schools. This is in part due to the very large range of results from 60.0 to 2650.0, making the |Δave| very high.

For the students to measure pH and EC, a meter that is capable of measuring multiple parameters was used. Schools who participated in year one were provided with Eutech Waterproof Multi-Parameter Water Tester while schools who participated in year two were provided with an Oakton PCTSTestr. Even though the brand of these two probes are different, each can test for pH and EC using the same technology and techniques. Providing buffers for each test, the procedures for calibration are identical. Yet using the same device produces varying results. The pH R^2 values were well below the 0.50 mark, where R^2 has 0.50 as the middle marker, by definition. While the EC R^2 values turned out to be well above the 0.50 mark. And, the pH $|\Delta ave|$ values were often less than 1 while the EC $|\Delta ave|$ values were often above 100 due to the difference in range. An additional reason for these differences in correlations is due to the testing that the students did, as they were directly from the source, in the field, with no travel/storage time. Even with controlled environments, the storage and duration may have influenced each sample before it being tested by the laboratory.

3.8 Copper, iron and manganese

Not every analyte was able to be correlated using R^2 and $|\Delta ave|$. Results being produced by WSL for copper, iron and manganese fell well below the detection limit from the chemistry kits used by the students (Table 2 found in M&M chapter). To be considered within range (WR), a WSL result needs to be within 0.05 mg/L for HS results of copper and iron and a WSL result within 4.5 mg/L for HS results of manganese (Table 5).

To correlate the results from Table 5, a color correlation approach can be observed in Table 6. The majority of results were WR 100% (green), yet iron showed the to be the most challenging, even with 70% (red) as its lowest correlation, followed by copper with 74%. Manganese proved to be the most with 100% WR due to its larger range of acceptable WR at 4.5 mg/L compared to copper and irons' acceptable WR at

0.05 mg/L. These were once again up to the students to make visual judgments using the provided comparators. Students experienced similar challenges testing for coper, iron and manganese as they did testing for nitrate-N. Similarly, correlated results came out indicating the students' use of these chemistry kits were effective even with limitations.

The R^2 values for EC were good due to their nearness to 1.0. However the $|\Delta ave|$ values for EC were not great due to their large numbers further away from zero. The R^2 values for pH were not great due to their nearness to zero. However the $|\Delta ave|$ values for pH were good due to their low numbers closer to zero. Results for nitrate were stable in a sense due to the R^2 values being mid range yet closer to 1.0 rather than zero, and the $|\Delta ave|$ values not being as high as EC's and as low as pH's. Nitrate did not have the dramatic variance in range like pH and EC did and therefore R^2 and $|\Delta ave|$ values were not polar opposites.

Previous studies of citizen science and water quality have some aspects similar to this project. In previous studies, comparison between citizen science data and professional data has been done via analysis of variance, repeatability and reproducibility, difference diagrams, method trueness and precision, bubble, spider and box-whisker plots, Kapa and B statistic, and the coefficient of determination. In one such study, Muenich et al. (2016) had similarities in having citizens collect samples in the Wabash River Watershed. The collected samples were similarly tested by both the citizen scientists and again by professional scientists for purposes of QA/QC. They tested for similar analytes such as nitrate and pH. However, the differences between Muenich's study and this one are that they sampled surface water instead of groundwater, was a five year study instead, and used adults from the community instead of HS students as citizen scientists. The citizen scientists in the Wabash River Watershed used test strips to determine results whereas in this study chemistry kits were utilized (Muenich et al., 2016). In Muenich et al. (2016), results were represented in different statistical methods. Muenich utilized percent agreement, bubble plots, Kapa and B Statistic to compare the results produced between their citizen scientists and professional scientists, where this study utilized percent agreement, boxplots, R^2 and differences in $|\Delta ave|$ (|HS average – WSL average|). The percent agreement used in Muenich's study, similarly used in this one, also had percent agreement results in the 80s and 90s. However, boxplots and spider plots were utilized to demonstrate the special distribution of the results and not the comparison between citizen scientists and professional scientists.

Another previous study was done by Peckenham and Peckenham (2014) with citizen scientists from New England. Similarly, in Peckenham's study, the citizen scientists were HS students and they sampled and tested for water quality from groundwater in their communities. However similar Peckenham's study may be, their method of QA/QC was very different. The citizen scientists did not have professional scientists to check comparability on results. Rather, the testing of the collected samples were tested with repeatability in duplicates and blanks as well as known concentrations and standards. Such a study produced statistics in the form of different diagrams and method trueness, the closeness of agreement between the average values (Menditto et al., 2007).

Another previous study was done by Weigelhofer et al. (2019) with citizen scientists as HS students in Austria. The students were able to test surface water for phosphorous concentrations alone. Students were able to run replicates as a means of QA/QC. The professional laboratory was able to test the students' replicates and determine a coefficient of determination (Weigelhofer et al., 2019).

The difference between Peckenham's study and this one is the involvement of a professional laboratory testing every sample the citizen scientists test for purposes of QA/QC. Meunich's study focused on surface water and non-HS student participants as citizen scientists. Weigelhofer's study also focused on surface water rather than groundwater, but did utilize HS students and used a professional laboratory, but not to compare every sample the students tested. Each had their own methods to test for comparability and each different than this study.

The effectiveness of citizen science in this study can be seen in comparing results from the citizen scientists and the professional laboratory. For data to be effective in R^2, it should be high, whereas $|\Delta ave|$ should be low. Even though pH and EC were tested by the citizen scientists on the same testing apparatus, the R^2 values and the $|\Delta ave|$ values were different due to range. With pH having low R^2 values and low $|\Delta ave|$ values, EC had high values for both R^2 and $|\Delta ave|$.

CHAPTER 4

CONCLUSION AND RECOMMENDATIONS

As seen with the multiple parameters used in this project, results show that citizen science can be effective in monitoring groundwater quality, but still needs improvement. Observing HS students use non-analytical instrumentation and produce even some results similar to that of the WSL indicates that high quality and effective citizen science is possible. Even with limitations in resources and experience, the HS and WSL results showed similarities with correlations from R^2, $|\Delta ave|$ and box-whisker. However, this wasn't the case for all parameters. Copper, manganese and nitrate-N measurements showed the greatest similarities in all correlation approaches. EC showed similarities in R^2 and differences in $|\Delta ave|$, but vise-versa when it came to pH. Calcium hardness, chloride and iron showed the greatest differences in all correlation analyses.

With differences in correlation across all parameters, a variety of approaches can be pursued in order to better validate and improve the role of citizen science in groundwater quality sciences. To produce a better correlation between citizen scientists and professional scientists, human error needs to be addressed. To start, some or all of the equipment that the citizen scientists use can be analytical instrumentation, which would initially add to equipment and training cost and time, especially to first time HS teachers participating in such study. Practices of titration and ampule chemistry can presently be replaced with a handheld multi-analyte photometer due to ongoing advancements in technology and its affordability. This would level the approaches between citizen scientists and professional scientists by having both parties utilize analytical instrumentation, lowering the probability of human error from citizen scientists.

Practices that are considered standard in a professional laboratory should be introduced to the routine of citizen scientists. The citizen scientists were confined to the limits of the chemistry kits without an introduction to the practice of dilution, which were also found in professional laboratories, yet the practice of dilution allowed professional scientists to generate results greater than the provided limits. QA/QC are various practices that are standard in professional laboratories and should also be introduced to citizen scientists in order to strengthen validation potential. Simplifications of QA/QC practices such as testing duplicate, blank and spiked samples can add validity to citizen science.

Professional scientists and citizen scientists are two parties that have mutual goals in progressing the understanding of sciences. In order to reach success, effective communication is a necessity. The more transparent the communication and the more welcoming it can be, an understanding between the two parties may suggest progress in scientific progress. Technology can help, but it can also backfire. To have a proactive approach in the potential benefits from technology such as websites, social media and applications, there needs to be an understanding of its uses, its users and the constant evolution towards perfection. People change, including professional scientists and citizen scientists, as well as science itself. Technology that attempts to help in scientific communication needs to proactively improve with its uses and its users.

Citizen science is showing progress and hope in the validation of its sciences, especially in the groundwater sciences. Though not perfect, with suggested improvements and most importantly, with cooperation and collaboration among its professional fields, citizen science can improve science for all and science in itself. Citizen science, though it can produce immediate results as seen in this research, its greater strength of investment will be found in the long term as citizens will contribute to the development of the sciences, future scientists, better-informed citizens and a better understanding of science by citizens.

REFERENCES

Alender, Bethany J. 2015. “Understanding Volunteer Motivations to Participate in Citizen Science Projects: A Deeper Look at Water Quality Monitoring.” The Evergreen State College.

Know Your Well Project App. https://itunes.apple.com/us/app/know-your-well/id1278672864?mt=8. [Accessed on 01/23/2020].

Brouwer, Stijn, Paul W.J.J. van der Wielen, Merijn Schriks, Maarten Claassen, and Jos Frijns. 2018. “Public Participation in Science: The Future and Value of Citizen Science in the Drinking Water Research.” *Water (Switzerland)* 10 (3): 1–15. https://doi.org/10.3390/w10030284.

Buytaert, Wouter, Zed Zulkafli, Sam Grainger, Luis Acosta, Tilashwork C. Alemie, Johan Bastiaensen, Bert De B., et al. 2014. “Citizen Science in Hydrology and Water Resources: Opportunities for Knowledge Generation, Ecosystem Service Management, and Sustainable Development.” *Frontiers in Earth Science* 2 (October): 1–21. https://doi.org/10.3389/feart.2014.00026.

Caruana, Rich, Mohamed Elhawary, Art Munson, Mirek Riedewald, Daria Sorokina, Daniel Fink, Wesley M. Hochachka, and Steve Kelling. 2006. “Mining Citizen Science Data to Predict Orevalence of Wild Bird Species.” *Proceedings of the 12th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining - KDD ’06*, 909. https://doi.org/10.1145/1150402.1150527.

Central District Health Department. 2019. “Water Testing.” https://cdhd.ne.gov/what-we-do/water-testing.html. [Accessed on 03/05/2020].

Chase, Sarah K., and Arielle Levine. 2016. “A Framework for Evaluating and Designing Citizen Science Programs for Natural Resources Monitoring.” *Conservation Biology* 30 (3): 456–66. https://doi.org/10.1111/cobi.12697.

Choo, Gyo-Hwang, Jeonghyeon Seo, Jongmin Yoon, Deok-Rae Kim, and Dong-Won Lee. 2020. “Analysis of Long-Term (2005–2018) Trends in Tropospheric NO2 Percentiles over Northeast Asia.” *Atmospheric Pollution Research*.

“Christmas Bird Count.” 2018. https://www.audubon.org/conservation/science/christmas-bird-count%0D. [Accessed 02/19/201].

Conrad, Cathy C., and Krista G. Hilchey. 2011. “A Review of Citizen Science and Community-Based Environmental Monitoring: Issues and Opportunities.” *Environ Monit Assess*, 273–91.

Craglia, Max, and Carlos Granell. 2014. *Citizen Science and Smart Cities - Report of Summit*. https://doi.org/10.2788/80461.

Dickinson, Janis L., Jennifer Shirk, David Bonter, Rick Bonney, Rhiannon L. Crain, Jason Martin, Tina Phillips, and Karen Purcell. 2012. “The Current State of Citizen Science as a Tool for Ecological Research and Public Engagement.” *Frontiers in Ecology and the Environment* 10 (6): 291–97. https://doi.org/10.1890/110236.

Dunn, Erica H, Charles M Francis, Peter J Blancher, Susan Roney Drennan, Marshall A Howe, Denis Lepage, Chandler S Robbins, Kenneth V Rosenberg, John R Sauer, and Kimberly G Smith. 2005. “Enhancing the Scientific Value of the Christmas Bird Count.” *The Auk* 122 (1): 338–46. https://doi.org/10.1642/0004-8038(2005)122[0338:ETSVOT]2.0.CO;2.

Durrance, Joan C. 1984. “Armed for Action: Library Response to Citizen Information Needs.” Neal Schuman Pub.

Fetter, C. W. 2018. *Applied Hydrogeology*. 4th ed. Oshkosh, Wisconsin: Waveland Press. https://books.google.com/books?hl=en&lr=&id=BYZXDwAAQBAJ&oi=fnd&pg=PP1&dq=c.w.+fetter+2018&ots=kF1EbrYdJT&sig=yKOpfPgm76OR1Hp1nwHVQgmGrZI#v=onepage&q=c.w. fetter 2018&f=false.

Gleick, Peter H. 1998. “Water in Crisis: Paths to Sustainable Water Use.” *Ecological Applications* 8 (3): 571–79. https://doi.org/10.1890/1051-0761(1998)008[0571:WICPTS]2.0.CO;2.

Grace-McCaskey, Cynthia, Alex K. Manda, James Randall Etheridge, and Jennifer O’Neill. 2017. “A Citizen Science Approach to Groundwater Monitoring: The Impacts of Participation on Knowledge and Attitudes, and Implications for Management.” In *Neurobehav.Toxicol.Teratol*. Vol. 49. Seattle: GSA.

Hannibal, Mary Ellen. 2017. *Can Citizen Science Save Us?* USA: TEDxStanford. https://youtu.be/SC2S_jkjUK0.

Ibe, A. Chidi, and Gunnar Kullenberg. 1995. “Quality Assurance/Quality Control (QA/QC) Regime in Marine Pollution Monitoring Programmes: The GIPME Perspective.” *Marine Pollution Bulletin* 31 (4–12): 209–13. https://www.sciencedirect.com/science/article/abs/pii/0025326X9500191O.

Isaac, Nick J.B., Arco J. van Strien, Tom A. August, Marnix P. de Zeeuw, and David B. Roy. 2014. “Statistics for Citizen Science: Extracting Signals of Change from Noisy Ecological Data.” *Methods in Ecology and Evolution* 5 (10): 1052–60. https://doi.org/10.1111/2041-210X.12254.

Jalbert, Kirk, and Abby J. Kinchy. 2016. “Sense and Influence: Environmental Monitoring Tools and the Power of Citizen Science.” *Journal of Environmental Policy and Planning* 18 (3): 379–97. https://doi.org/10.1080/1523908X.2015.1100985.

Jordan, Rebecca C., Heidi L. Ballard, and Tina B. Phillips. 2012. “Key Issues and New

Approaches for Evaluating Citizen-Science Learning Outcomes.” *Frontiers in Ecology and the Environment* 10 (6): 307–9. https://doi.org/10.1890/110280.

Juntakut, Pongpun, Daniel D. Snow, Erin M.K. Haacker, and Chittaranjan Ray. 2019. “The Long Term Effect of Agricultural, Vadose Zone and Climatic Factors on Nitrate Contamination in the Nebraska’s Groundwater System.” *Journal of Contaminant Hydrology* 220 (January 2018): 33–48. https://doi.org/10.1016/j.jconhyd.2018.11.007.

Kawrykow, Alexander, Gary Roumanis, Alfred Kam, Daniel Kwak, Clarence Leung, Chu Wu, Eleyine Zarour, Luis Sarmenta, Mathieu Blanchette, and Jérôme Waldispühl. 2012. “Phylo: A Citizen Science Approach for Improving Multiple Sequence Alignment.” *PLoS ONE* 7 (3). https://doi.org/10.1371/journal.pone.0031362.

Kim, Sunyoung, Christine Robson, Thomas Zimmerman, Jeff Pierce, and Eben M. Haber. 2011. “Creek Watch: Pairing Usefulness and Usability for Successful Citizen Science.” *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 2125–34. https://doi.org/10.1017/CBO9781107415324.004.

“Know Your Well.” https://knowyourwell.unl.edu. [Accessed on 04/16/2019].

Kosmala, Margaret, Andrea Wiggins, Alexandra Swanson, and Brooke Simmons. 2016. “Assessing Data Quality in Citizen Science.” *Frontiers in Ecology and the Environment* 14 (10): 551–60. https://doi.org/10.1002/fee.1436.

Le-Gratiet, Bertrand, Régis Bouyssou, Julien Ducoté, Alain Ostrovsky, Charlotte Beylier, Christian Gardin, Nivea Schuch, et al. 2020. “Contour Based Metrology: ‘Make Measurable What Is Not So.’” *Etrology, Inspection, and Process Control for Microlithography* 11325. https://doi.org/10.1117/12.2551907.

Link, William A., John R. Sauer, and Daniel K. Niven. 2006. “A Hierarchical Model for Regional Analysis of Population Change Using Christmas Bird Count Data, with Application to the American Black Duck Population Change using Christmas Bird Count.” *The Condor* 108 (1): 13–24. https://doi.org/10.1650/0010-5422(2006)108[0013:AHMFRA]2.0.CO;2.

Marshall, Philip J., Chris J. Lintott, and Leigh N. Fletcher. 2015. “Ideas for Citizen Science in Astronomy.” https://doi.org/10.1146/annurev-astro-081913-035959.

Mattson, Kevin. 1998. “Creating a Democratic Public: The Struggle for Urban Participatory Democracy During the Progressive Era.” *Penn State Press*.

McCaffey, Rachel E. 2005. “Using Citizen Science in Urban Bird Studies *.” *Methods* 3 (1).

Mckinley, Duncan C, Abe J Miller-rushing, Heidi L Ballard, Rick Bonney, Hutch Brown, Susan C Cook-patton, Daniel M Evans, et al. 2017. “Citizen Science Can Improve Conservation Science , Natural Resource Management , and Environmental Protection” 208: 15–28. https://doi.org/10.1016/j.biocon.2016.05.015.

Menditto, Antonio, Marina Patriarca, and Bertil Magnusson. 2007. “Understanding the Meaning of Accuracy, Trueness and Precision.” *Accreditation and Quality Assurance* 12 (1): 45–47. https://doi.org/10.1007/s00769-006-0191-z.

Muenich, Rebecca Logsdon, Sara Peel, Laura C. Bowling, Megan Heller Haas, Ronald F. Turco, Jane R. Frankenberger, and Indrajeet Chaubey. 2016. “The Wabash Sampling Blitz: A Study on the Effectiveness of Citizen Science.” *Citizen Science: Theory and Practice* 1 (1): 3. https://doi.org/10.5334/cstp.1.

Nakagawa, Shinichi, Paul C.D. Johnson, and Holger Schielzeth. 2017. “The Coefficient of Determination R2 and Intra-Class Correlation Coefficient from Generalized Linear Mixed-Effects Models Revisited and Expanded.” *Journal of the Royal Society Interface* 14 (134). https://doi.org/10.1098/rsif.2017.0213.

NDEQ. “2018 Nebraska Groundwater Quality Monitoring Report.” [Accessed on 08/02/2019]

Nebraska Department of Natural Resources. “Groundwater.” [Accessed on 03/02/2020] https://dnr.nebraska.gov/groundwater.

Newman, Greg, Andrea Wiggins, Alycia Crall, Eric Graham, Sarah Newman, and Kevin Crowston. 2012. “The Future of Citizen Science: Emerging Technologies and Shifting Paradigms.” *Frontiers in Ecology and the Environment* 10 (6): 298–304. https://doi.org/10.1890/110294.

Nov, Oded, Ofer Arazy, and David Anderson. 2011. “Technology-Mediated Citizen Science Participation: A Motivational Model.” In *Proceedings of the Fifth International AAAI Conference on Weblogs and Social Media*, 147–63.

Orange County. 2014. “OCWA.” http://waterauthority.orangecountygov.com/education_getwet.html. [Accessed on 01/22/2019].

Pahl-Wostl, Claudia. 2009. “A Conceptual Framework for Analysing Adaptive Capacity and Multi-Level Learning Processes in Resource Governance Regimes.” *Global Environmental Change* 19 (3): 354–65. https://doi.org/10.1016/j.gloenvcha.2009.06.001.

Peckenham, John M., and Sarah K. Peckenham. 2014. “Assessment of Quality for Middle Level and High School Student-Generated Water Quality Data.” *Journal of the American Water Resources Association* 50 (6): 1477–87. https://doi.org/10.1111/jawr.12213.

Postel, Sandra. 2013. *The Last Oasis Facing Water Scarcity*. *Worldwatch*. https://content.taylorfrancis.com/books/download?dac=C2011-0-06759-3&isbn=9781134161584&format=googlePreviewPdf.

Prince, M. 2004. "Does Active Learning Work? A Review of the Research." *Journal of Engineering Education* 93 (3): 223–31.

Ramirez-andreotta, Mónica D, Mark L Brusseau, Janick Artiola, Raina M Maier, and a Jay Gandolfi. 2015. "Building a Co-Created Citizen Science Program with Gardeners Neighboring a Superfund Site: The Gardenroots Case Study." *International Public Health Journal* 7 (1): 1–18. http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=4420190&tool=pmcentrez&rendertype=abstract.

Ranard, Benjamin L., Yoonhee P. Ha, Zachary F. Meisel, David A. Asch, Shawndra S. Hill, Lance B. Becker, Anne K. Seymour, and Raina M. Merchant. 2013. "Crowdsourcing—Harnessing the Masses to Advance Health and Medicine, a Systematic Review." *Journal of General Internal Medicine*, 187–203. https://doi.org/10.1007/s11606-013-2536-8.

Resnik, David B., Kevin C. Elliott, and Aubrey K. Miller. 2015. "A Framework for Addressing Ethical Issues in Citizen Science." *Environmental Science and Policy* 54: 475–81. https://doi.org/10.1016/j.envsci.2015.05.008.

Şekercioĝlu, Çaĝan H. 2012. "Promoting Community-Based Bird Monitoring in the Tropics: Conservation, Research, Environmental Education, Capacity-Building, and Local Incomes." *Biological Conservation* 151 (1): 69–73. https://doi.org/10.1016/j.biocon.2011.10.024.

Silvertown, Jonathan. 2009. "A New Dawn for Citizen Science." *Trends in Ecology and Evolution*, 467–71. http://dx.doi.org/10.1007/978-94-007-4587-2_7.

Thornton, Teresa E. 2014. "GET WET!" http://getwetproject.org/StatePrograms.html. [Accessed on 12/03/2018].

Thornton, Teresa, and Jessica Leahy. 2012. "Trust in Citizen Science Research: A Case Study of the Groundwater Education Through Water Evaluation & Testing Program." *Journal of the American Water Resources Association* 48 (5): 1032–40. https://doi.org/10.1111/j.1752-1688.2012.00670.x.

Turner, Dale S., and Holly E. Richter. 2011. "Wet/Dry Mapping: Using Citizen Scientists to Monitor the Extent of Perennial Surface Flow in Dryland Regions." *Environmental Management* 47 (3): 497–505. https://doi.org/10.1007/s00267-010-9607-y.

USDA. "2018 State Agriculture Overview - Nebraska." https://www.nass.usda.gov/Quick_Stats/Ag_Overview/stateOverview.php?state=NE

BRASKA. [Accessed on 02/03/2020]

USGS. 2020. "How Much Water Is There on Earth?" Water Science School. 2020. https://www.usgs.gov/special-topic/water-science-school/science/how-much-water-there-earth?qt-science_center_objects=0#qt-science_center_objects.

Weigelhofer, Gabriele, Eva Maria Pölz, and Thomas Hein. 2019. "Citizen Science: How High School Students Can Provide Scientifically Sound Data in Biogeochemical Experiments." *Freshwater Science* 38 (2): 236–43. https://doi.org/10.1086/698765.

Wiggins, Andrea, and Kevin Crowston. 2011. "From Conservation to Crowdsourcing: A Typology of Citizen Science." *Proceedings of the Annual Hawaii International Conference on System Sciences*, 1–10. https://doi.org/10.1109/HICSS.2011.207.

Zhang, Dabao. 2017. "A Coefficient of Determination for Generalized Linear Models." *American Statistician* 71 (4): 310–16. https://doi.org/10.1080/00031305.2016.1256839.

Appendices

APPENDIX A

Pre-Field Activity

(Name) High School
Today's date:
Recorder's name:
Questions for the well owner/user
-Name of the resident well user:
-Address:
-City:
-Zip code:
-Well owner (if different from resident):
-When was the well installed?
-Any complaints about smell or taste of water?
-Does the well ever go dry? (if so, when?)
-Any maintenance done to the well itself within the last five years?
-Any major land use / development changes around the well within the last five years?
-How many people use this well?
-Has any manure or pesticides been applied near the well within the last five years?

Information that might be available on line (or by the well owner/user)
-Well GPS Coordinates:
-Bore hole diameter:
-Total depth of well:
-Water level:
-Well construction completed:
-Drilling method:
-Aquifer type: Confined / Unconfined
-Aquifer class: Bedrock / Sand or gravel
-Well type (construction method): Drilled / Driven / Dug
- What is the well casing material made of?

Field Activity

(Name) High School
Name of observer(s) / recorder(s):

Well ID:	Today's date:

Describe the settings:
(the weather, temperature, how your feeling, anything that should be noted or expressed)
On-site observations

GPS coordinates for the: (use App if able)	Latitude	Longitude
Well Head		
nearest surface water (lake, pond, creek, river, etc.)		
nearest cropland		
nearest barnyard or pasture		
nearest septic system		

-Topography of well location:
hill top / hill slope / level land / depression
-Condition of well cover:
intact / observable openings / damaged
-Is there evidence for surface run-off entry into the well?
-Is there evidence of pooling/puddling within 12 feet of the well?

Readings (multimeter)

Groundwater temperature: (Celsius)	
pH :	
Conductivity : (µs/cm)	

Anything else to note?

<u>High School Laboratory Tests</u>

(Name) High School
<u>Sample ID</u>
Ammonia: __________ [0 – 10 ppm (mg/L)]
-additional observations:
Pesticides (Atrazine): _________ [positive / negative (to more than 3 ppb of atrazine)]
-additional observations:
Calcium Hardness: __________ [50 – 500 ppm (mg/L)]
-additional observations:
Chloride: __________ [0 – 400 ppm (mg/L)]
-additional observations:
Bacteria (Colilert): __________ [positive / negative (to more than 1 MPN / 100 mL)]
-additional observations:
Copper: __________ [0 – 10 ppm (mg/L)]
-additional observations:
Iron: __________ [0 – 10 ppm (mg/L)]
-additional observations:
Manganese: __________ [0 – 50 ppm (mg/L)]
-additional observations:
Nitrate: __________ [0 – 45 ppm (mg/L)]
-additional observations:
Nitrite: __________ [0 – 2.5 ppm (mg/L)]
-additional observations:

APPENDIX B

Ammonia CHEMets Kit

K-1510

https://www.chemetrics.com/product/ammonia-chemets-kit-2/

https://chemetrics.b-cdn.net/uploads/2019/01/i1510.pdf

Atrazine Strip Test Kit (Abraxis)

PN 500009

https://abraxis.eurofins-technologies.com/home/products/rapid-test-kits/pesticides-herbicides/pesticide-test-strip-kits/atrazine-dipstick-20-test/

https://abraxis.eurofins-technologies.com/media/6304/atrazine-strip-r110519.pdf

Bacteria (total coliforms and E. coli)

IDEXX Colilert

https://www.idexx.com/en/water/water-products-services/colilert/

https://www.idexx.com/files/colilert-procedure-en.pdf

Calcium Hardness Tirets Kit (CHEMets)

K-1705

https://www.chemetrics.com/product/hardness-calcium-titrets-titration-cells/

https://chemetrics.b-cdn.net/uploads/2019/01/i1705.pdf

Chloride Test Kit (HACH)

Model 8-P Cat. No. 1440-01

https://www.hach.com/chloride-low-range-test-kit-model-8-p/product-downloads?id=7640219502

Copper CHEMets Kit

K-3510

https://www.chemetrics.com/product/copper-soluble-chemets-visual-kit/

https://chemetrics.b-cdn.net/uploads/2019/10/i3510.pdf

Iron CHEMets Kit

K-6010

https://www.chemetrics.com/product/iron-total-soluble-chemets-visual-kit-k-6010/

https://chemetrics.b-cdn.net/uploads/2019/11/i6x10.pdf

Manganese VACUettes Kit (CHEMets)

K-6502D

https://www.chemetrics.com/product/manganese-vacuettes-visual-high-range-kit/

https://chemetrics.b-cdn.net/uploads/2019/01/i6502d.pdf

Nitrate CHEMets Kit

K-6909D

https://www.chemetrics.com/product/nitrate-test-kit-chemets-visual-kit-k6909d/

https://chemetrics.b-cdn.net/uploads/2019/11/i6909a_d.pdf

Nitrite CHEMets Kit

K-7004

https://www.chemetrics.com/product/nitrite-chemets-visual-kit-k-7004/

https://chemetrics.b-cdn.net/uploads/2019/01/i7004.pdf

Ph and electroconductivity

Hanna Instruments Multiparameter Tester / Oakton PCTSTester

https://www.coleparmer.com/i/oakton-pctstestr-50-waterproof-pocket-ph-cond-tds-salinity-tester-premium-50-series/3563435

https://pim-resources.coleparmer.com/instruction-manual/1065o100-man-35634-35-final.pdf

APPENDIX C

Equipment	SOP Number	SOP Author
pH Meter	03_05_01.001	Suzanne Polzkill
Conductivity Meter	03_03_01.001	Suzanne Polzkill, Tania Biswas
AQ2	02_01_01.001 02_03_01.003	Tania Biswas Tania Biswas
IC	10_01_01.007	Tania Biswas
AA	01_02_01.003	Nathan Roddy, Tania Biswas
ICP-MS	09_01_01.002	Tania Biswas
GC-MS	06_01_01.004	Dave Cassada

IDEXX Colilert Procedure Manual: http://www.idexx.com/resource-library/water/colilertprocedure-en.pdf.

APPENDIX D

Nitrate

High School		a	b	R^2	n	R^2 Average		Standard Deviation	
Year 1	Oak	1.7384	-3.113	0.8113	20	0.5722	0.6323	0.3394	0.2552
	Maple	0.7637	6.7233	0.3444	18				
	Ash	0.5618	6.5142	0.2227	19				
	Aspen	0.996	1.1551	0.9104	13				
Year 2	Birch	1.0392	2.9196	0.5894	7	0.6723		0.2080	
	Sycamore	0.5476	0.3048	0.3351	10				
	Willow	1.1132	2.0613	0.722	16				
	Chestnut	0.5061	4.013	0.6828	15				
	Cottonwood	0.9773	1.0929	0.9714	20				
	Elm	0.7828	0.4871	0.7332	5				

Calcium Hardness

High School		a	b	R^2	n	R^2 Average		Standard Deviation	
Year 1	Oak	1.9168	-64.53	0.7992	20	0.3451	0.3794	0.3277	0.3380
	Maple	0.5618	116.88	0.33	18				
	Ash	0.1874	221.16	0.0275	19				
	Aspen	0.3058	208.17	0.2236	13				
Year 2	Birch	1.2698	-12.137	0.7875	7	0.4023		0.3737	
	Sycamore	-0.0955	363.85	0.0011	10				
	Willow	-0.297	365.6	0.0662	16				
	Chestnut	0.6368	122.41	0.4437	15				
	Cottonwood	0.5685	183.41	0.2217	20				
	Elm	1.1873	-16.889	0.8938	4				

Chloride									
High School		a	b	R^2	n	R^2 Average		Standard Deviation	
Year 1	Oak	0.6796	-18.684	0.9853	20	0.4986	0.3664	0.3781	0.3470
	Maple	0.3214	-2.3915	0.3849	18				
	Ash	0.5097	-14.944	0.5461	19				
	Aspen	0.1138	10.159	0.078	14				
Year 2	Birch	0.036	2.2776	0.02	7	0.2784		0.3282	
	Sycamore	0.2148	0.6733	0.1971	10				
	Willow	0.3244	-1.7739	0.5381	16				
	Chestnut	-0.0751	17.488	0.069	11				
	Cottonwood	0.4275	-35919	0.818	20				
	Elm	-0.0167	3.0601	0.0279	6				

pH									
High School		a	b	R^2	n	R^2 Average		Standard Deviation	
Year 1	Oak	0.4545	4.0672	0.1912	20	0.3048	0.2678	0.2500	0.2836
	Maple	0.3537	4.6768	0.2383	16				
	Ash	0.8761	1.1347	0.6723	4				
	Aspen	-0.9843	14.562	0.1173	14				
Year 2	Birch	0.7079	2.0716	0.6212	13	0.2431		0.3248	
	Sycamore	0.0441	6.8632	0.005	10				
	Willow	0.0002	7.1995	0	14				
	Chestnut	0.3325	4.6507	0.1411	18				
	Cottonwood	0.0276	7.0813	0.0012	20				
	Elm	0.5936	2.7534	0.69	7				

Electrical conductivity									
High School		a	b	R^2	n	R^2 Average		Standard Deviation	
Year 1	Oak	0.9945	37.166	0.9091	20	0.7081	0.8231	0.4007	0.2541
	Maple	0.7231	89.862	0.804	16				
	Ash	1.4353	-386.99	1	2				
	Aspen	-0.5482	902.65	0.1192	14				
Year 2	Birch	0.7142	4.5522	0.8349	13	0.8997		0.0481	
	Sycamore	0.7282	89.495	0.9533	10				
	Willow	0.888	-49.853	0.9531	14				
	Chestnut	0.9678	-42.252	0.8821	18				
	Cottonwood	0.865	-8.6192	0.8648	20				
	Elm	0.9446	-13.274	0.9101	7				

Nitrate			|WSL - HS|		n
High School		R^2	Average	Stand. Dev.	
Year 1	Oak	0.680	5.24	11.42	20
	Maple	0.344	6.74	7.95	18
	Ash	0.223	11.25	13.27	19
	Aspen	0.910	1.18	1.54	13
Year 2	Birch	0.589	3.19	5.83	7
	Sycamore	0.335	1.38	1.29	10
	Willow	0.722	3.50	4.48	16
	Chestnut	0.683	4.45	5.46	15
	Cottonwood	0.971	1.40	1.38	20
	Elm	0.733	1.35	0.60	5
Calcium Hardness			**|WSL - HS|**		**n**
High School		R^2	**Average**	**Stand. Dev.**	
Year 1	Oak	0.799	170.09	144.31	20
	Maple	0.330	91.76	79.26	18
	Ash	0.028	109.44	89.16	19
	Aspen	0.224	120.31	68.13	13
Year 2	Birch	0.788	39.86	80.23	7
	Sycamore	0.001	172.24	177.04	10
	Willow	0.066	211.76	128.66	16
	Chestnut	0.444	70.19	70.78	15
	Cottonwood	0.222	92.13	77.69	20
	Elm	0.894	10.80	8.54	4
Chloride			**|WSL - HS|**		**n**
High School		R^2	**Average**	**Stand. Dev.**	
Year 1	Oak	0.985	43.03	37.43	20
	Maple	0.385	37.30	15.91	18
	Ash	0.546	56.80	29.11	19
	Aspen	0.078	43.94	72.14	14
Year 2	Birch	0.020	31.32	2.50	7
	Sycamore	0.197	21.39	10.73	10

	Willow	0.538	22.32	13.08	16
	Chestnut	0.069	41.15	49.50	11
	Cottonwood	0.818	23.03	18.68	20
	Elm	0.028	49.81	26.10	6
pH			**|WSL - HS|**		**n**
High School		**R^2**	**Average**	**Stand. Dev.**	
Year 1	Oak	0.191	0.24	0.23	20
	Maple	0.238	0.42	0.47	16
	Ash	0.672	2.15	3.76	4
	Aspen	0.117	0.89	0.62	14
Year 2	Birch	0.621	0.21	0.29	13
	Sycamore	0.005	0.27	0.32	10
	Willow	0.000	0.86	2.65	14
	Chestnut	0.141	0.17	0.18	18
	Cottonwood	0.001	0.20	0.22	20
	Elm	0.690	0.21	0.15	7
Electrical conductivity			**|WSL - HS|**		**n**
High School		**R^2**	**Average**	**Stand. Dev.**	
Year 1	Oak	0.909	129.60	91.19	20
	Maple	0.804	178.38	161.70	16
	Ash	1.000	139.50	21.92	2
	Aspen	0.119	416.54	240.98	14
Year 2	Birch	0.835	102.27	144.54	13
	Sycamore	0.953	137.75	121.34	10
	Willow	0.953	139.79	63.67	14
	Chestnut	0.882	76.17	48.92	18
	Cottonwood	0.865	116.30	73.11	20
	Elm	0.910	38.71	30.57	7